In Search of Working Time? Hours Constraints, Firms and Mobility*

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Abstract

Can workers reach their preferred working hours over time? This paper provides novel empirical evidence on hours constraints—barriers for workers to work their preferred hours at a given wage rate—by linking self-reported hour preferences from large-scale survey data with administrative employer-employee data between 2003 and 2023. Twenty percent of French salaried workers report wanting to increase their hours at their given wage. Leveraging the panel dimension of my data, I show that constrained workers switch employers more frequently and experience increases in hours and earnings through mobility. However, most constrained workers remain unable to adjust their hours over time, particularly low-wage and female workers. Next, I develop a revealed preference method to estimate welfare effects associated with constraints and find that workers would on average require a 1.6% wage increase to be as well off as when working their ideal hours. These findings highlight the important role of hours worked as a job amenity in shaping labor market sorting.

Keywords: Working Hours, Labor Supply, Hours Constraints.
JEL Codes: J22, J31, C81

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1 Introduction

Both a source of income and disutility, working hours are a central element of workers' lives. However, most workers cannot freely choose their hours, as first emphasized by Lewis (1967), since employers have a clear interest in the hours worked by their employees. This implies that several workers may be *constrained* in jobs where they cannot work their preferred number of hours. When unable to choose their hours within their current job, a crucial question is whether they can, and at what cost, relax their hours constraints.

This paper provides novel empirical evidence on the topic of hours constraints. Combining self-reported hours preferences from the French Labor Force Survey with panel employer-employee data, I can track workers after their report and observe their adjustments in hours and earnings over a large number of years. Using this unique data, I quantify welfare effects associated with constraints, i.e. how much workers would agree to lose (in hourly wage) to reach their optimal hours. The richness of my data also allows me to document several unexplored aspects of hours constraints, e.g. which workers are most able to close the gap to preferred hours or what type of labor market mobility favor adjustments in hours.

Hours constraints have received significant attention in the labor literature (see Kahn and Lang (2001) for an introduction). Empirical studies consistently find that a large proportion of workers are not working their desired hours, although the direction of constraints varies across countries. Jarosch et al. (2025) show in a recent paper that German and British workers tend to be *overworked*, or constrained from below, while US workers are mostly *underworked* or constrained from above. In the German case, more than two thirds of workers report wanting to work fewer hours. France exhibits a pattern closer to the US: evidence from the *Enquête Emploi*, the French Labor Force Survey, indicates that 20% of salaried workers would work more hours at their given wage rate, compared to 40% in the US (based on the RPS survey). Such magnitude points to hours constraints as a widespread labor market phenomenon.

A first question concerns the origins of constraints: what prevents workers from working their preferred hours? First, working hours are heavily regulated, particularly in France[1], which implies that employers may have to bear additional (overtime) costs to increase hours of their employees.

[1] See Breda et al. (2025) for more on the French working time regulation.

Second, early research (Altonji and Paxson, 1986; Dickens and Lundberg, 1993) emphasized the importance of occupation in hours practices. Certain jobs, e.g. train drivers or school teachers, are associated with specific hours requirements that may leave little room for adjustment. Recent work has rather focused on the role of firm-specific features, following the idea that hours worked likely depend on each firm's organization and technology. Kahn and Lang (2001) provide a broad discussion of the potential sources of firms' preferences over hours, e.g. highlighting the role played by coordination in team production contexts, as in Rosen (1986). Labanca and Pozzoli (2023) build on this idea to rationalize hours constraints as compensated by wage differentials arising from productivity gains. Lachowska et al. (2023) includes the most comprehensive theoretical framework to date for the study of constraints, using an extended version of the Lewis-Rosen model (Lewis, 1969; Rosen, 1974). Their findings point to the existence of a job ladder on wages and hours, i.e. a hierarchical ranking of employers based on job desirability, as the source of hours constraints, and conclude that long-hour jobs are too costly for most employers.

A second question concerns the welfare implications of constraints. Survey data suggest the distance to preferred hours may be large, particularly for part-time workers who mostly want to increase their hours to a full-time schedule. This implies that constrained workers may be far from their labor supply curve and would accept a large wage reduction to close the gap. Lachowska et al. (2023) take a revealed preference approach to estimate this gap and find that workers would on average require a 12% higher wage to be as well off as they would be while working their ideal hours. They also find a 15% average distance between actual and desired hours, consistent with survey data. Their methodology reflects the magnitude of welfare effects associated with constraints at the labor market level, but it does not identify revealed preference from actual workers' choices.

The lack of suitable data have made it difficult to address these questions. Preferences over hours are hard to identify, and aside from a few exceptions (Labanca and Pozzoli (2023) use a firm-level proxy based on the within-firm dispersion of hours, while Lachowska et al. (2023) take an aggregate approach relying on firms' estimated value and hours policies), the most common approach relies on surveys. However, surveys that directly elicit hours preferences are generally not panel data, with the notable exception of Jarosch et al. (2025), and are rarely linked to firm-level information. Moreover, their measures of hours and earnings are likely imperfect, as they typically rely on self-reported data rather than administrative records.

In this paper, I overcome previous data limitations by linking self-reported hour preferences from a large-scale survey with panel employer-employee data. I exploit the presence of establishments' identifiers in the French Labor Force Survey, conducted by Insee[2], and use them to link survey data to administrative records. As there are no common individual identifiers between both sources, I adopt a "1-to-1" matching approach based on variables such as age, gender or birth department combined with the firm identifier. This method allows me to retain information for a majority of surveyed salaried workers (67%, 435,472 individuals) between 2003 and 2023, capturing their self-reported hour preferences over six quarters and their administrative job characteristics, including paid hours and labor earnings, over a large number of years. By exploiting the panel structure of the administrative data, I can study the labor market trajectories of constrained workers and examine the welfare effects associated with their job changes. This unique linkage extends beyond the scope of hours constraints and contributes to bridging survey and administrative sources for economic research. The paper is then organized in three steps.

The first step examines the employment context of workers who report hours constraints to improve our understanding of the phenomenon. Hours-constrained workers are concentrated at the bottom of the wage distribution and primarily seek to increase earnings through additional work. Occupational sorting emerges as the dominant factor for part-time work, as involuntary part-time workers are heavily concentrated in few low-wage occupations that are intensive in part-time work. Firm sorting also plays an important role: evidence shows strong homogeneity in hours within firms but large heterogeneity between firms, even within a given occupation. Using an AKM (Abowd et al., 1999) decomposition to identify firm effects in both hours and wages, I find that constrained workers are disproportionately concentrated in firms offering low hours and low wages, consistent with the existence of a job ladder. Tackling the heterogeneity in hours inside of firms, I show evidence of worker segmentation over access to long-hour jobs associated with gender and experience.

The second part of the paper provides the first dynamic study of hours constraints at the worker-level. Leveraging the panel dimension of my data, I track the labor market trajectories of constrained workers in the years following their survey responses. I find that workers who want

[2] The French National Institute for Statistics and Economic Studies.

to increase their hours are more likely to switch employers shortly after their report. Using an event-study design, I estimate that constrained part-time workers increase their hours and earnings through mobility respectively by 6.3% and 5.5% as compared to prior unconstrained workers. Conversely, estimates are close to zero in the full-time group, showing that the experience of hours constraints likely differs across both types. The richness of my data also allows me to provide a thorough description of adjustment mechanisms. Workers are more likely to adjust their hours by switching occupation or moving to firms with long-hour policies, consistent with the prior identified role of occupational and firm rigidities. Despite evidence of large changes in hours, most constrained workers are likely not able to relax their constraints by 3 years after their report.

The third step develops a method to quantify workers' willingness to pay (WTP) for their preferred working hours, i.e. how much income they would sacrifice to work their optimal hours, building on the approach of Le Barbanchon et al. (2020) on the relation between wage and commute. The method takes advantage of workers' self-reported desired hours and of their subsequent employer-to-employer transitions. Workers start in an initial job with a given wage and hours, then report their preferred hours at that wage (as in the Labor Force Survey). I estimate the parameters of their utility function by finding the iso-utility curve that best explains which destination jobs they accept. Specifically, the method identifies the curve that minimizes the distance between accepted jobs that provide lower utility than the initial job and their projection onto that curve, as in Le Barbanchon et al. (2020). I solve the optimization problem using a grid search algorithm and find an average WTP equal to 1.6% of the current wage. This estimate is small as compared to Lachowska et al. (2023), as it is mostly driven by full-time workers whose changes in hours and wages are small. Next steps should include heterogeneous estimates for more or less constrained workers.

Related Literature. This work falls within a prominent, although specialized, literature on hour constraints. The theoretical foundations of hour constraints have been established in seminal work by Rosen (1974), then developed and refined (Abowd and Card, 1987; Dickens and Lundberg, 1993; Kahn and Lang, 2001; Bloemen, 2008). This literature intends to provide a framework in order to understand how hour constraints emerge and affect labor markets. The main reference from this literature for this paper is Lachowska et al. (2023), who builds on a revealed preference approach to quantify welfare effects of constraints. I contribute to this literature by combining a micro-level measure of hours constraints with administrative panel data to reassess important findings of this literature, including welfare effects.

This research also relates to a literature considering hours worked as a job amenity that influences workers' job choices and satisfaction. Hwang et al. (1998), Lang and Majumdar (2004), Lavetti and Schmutte (2016), Sorkin (2018), Lamadon et al. (2022), and Dube et al. (2022) have examined how hours worked affect workers' utility and job preferences. This paper adds to this body of work by estimating how much workers value their working hours.

Because of its relevance for the public economics literature, the relationship between hour constraints and labor supply responses to shocks has been largely explored. Kahn and Lang (1991) discusses the bias in labor supply elasticities due to the presence of hours constraints. Chetty et al. (2011) assess the implications of hours constraints for quasi-experimental estimation of labor supply elasticities. Labanca and Pozzoli (2022) show the unresponsiveness to tax changes in the context of hours constraints. This paper contributes to this literature by assessing the extent of hours rigidities in the labor market and whether they can be circumvented.

Lastly, this paper makes an important contribution to the measurement of true labor supply, to be distinguished from observed hours worked (Pencavel, 2015). The study of hours constraints complements extensive macroeconomic research (Costa, 2000; Bick et al., 2018, 2022) that directly interprets trends in hours worked as evidence of labor supply changes. Recent research by Jarosch et al. (2025) also belongs to this literature by estimating the implied macroeconomic effects of relaxing constraints. This paper reinforces the claim that hours constraints are a major feature of labor markets and should be invoked in all discussions related to working time.

The rest of the paper proceeds as follows. Section 2 presents the data, including the procedure to link the French Labor Force Survey to administrative data. Section 3 studies the employment contexts which favor the emergence of hours constraints. Section 4 tracks the evolution of constrained workers in the labor market, focusing on their ability to increase their hours and earnings. Section 5 estimates the workers' willingness-to-pay to relax their hours constraints based on a simple framework.

2 Data

I mobilize for the period between 2003 and 2023 two classic data sources for the study of the labor market in France: the French Labor Force Survey, the *EEC*, and the French matched employer-employee dataset, the *DADS*. Furthermore, both sources are used to build a newly matched dataset, the *EEC* $\times$ *DADS* which combines their information at the individual level. Beyond its purpose for this paper, this unique linkage constitutes an important contribution to the integration of survey and administrative datasets.

2.1 French Labor Force Survey (EEC)

The *Enquête Emploi en Continu* (EEC) is a large-scale nationally representative survey conducted by the French National Institute of Statistics and Economic Studies (*Insee*). Like every other European Labor Force Survey, it complies with the guidelines of the International Labour Office (ILO) and of Eurostat. Designed to provide a thorough understanding of the labor market dynamics, the EEC collects detailed information on workers' characteristics at a quarterly frequency for a maximum period of 6 quarters. The sample is restricted to non-agricultural salaried workers between 18 and 64 years old. Reported variables include standard demographic and labor market indicators such as age, municipality of residence, occupation, and labor earnings, as well as a broad range of measures capturing worker preferences. Hours worked, which are central to this paper, correspond to the usual number of hours per week[3]. Most importantly, the survey contains specific variables that I use to provide direct measures of hours constraints.

Hours constraints are measured using binary responses to questions (STPLC and STMN) asking workers whether they *"want to work* [more/less] *hours in their job with a corresponding* [increase/decrease] *in earnings"*. Workers who report they would want to work more or less are respectively denoted as constrained *from above* or *from below*, following the terminology of Lachowska et al. (2023). Workers who answer no to both questions are referred to as *unconstrained*. The specification *"with a corresponding income variation"* is designed to elicit workers' optimal hours at their current hourly wage, consistent with traditional labor supply models. The nonresponse rate is less than 1%, making this variable well-suited for analysis. When individuals respond affirmatively to either question, they are subsequently asked *"the number of hours that they would ideally*

[3] The EEC also includes the number of hours worked during the reference week in which the worker is surveyed. I do not use this variable as it relies too heavily on volatile parameters.

work with a corresponding income variation". This follow-up question yields a measure of desired hours for constrained workers, providing an intensive margin component to our constraint measures. In the group of workers constrained from above, I define as *involuntary part-time* workers the individuals who work part-time and report desired hours per week superior or equal to 35, which corresponds to the French reference duration. More than 70% of part-time workers constrained from above are in this case.

These questions appear in all European Labor Force Surveys, and have been frequently used to measure hours constraints in previous research (see e.g. Gaini and Vicard (2012); Beckmannschagen and Schröder (2022); Asai (2024) or more recently Jarosch et al. (2025)). However, the reliability of the answers can be questioned as common survey biases apply here (see Stantcheva (2023)). Understanding how workers perceive questions regarding the distance to their ideal hours, and whether their answers are truly indicative of constraints, is a priori challenging. Validity concerns are addressed to a certain extent by exploiting other survey information from the EEC. For instance, 95% of workers who report constraints from above report their availability to work more, the share being slightly higher for part-time workers. This provides evidence that constraints do not reflect mere preferences that are not in regard to real-life constraints (e.g. child caring). These workers have internalized their work environment and are ready to work more. Appendix B2 presents additional evidence on work motivations, persistence of preferences and worker mobility over the 6 quarters of observation to discuss the interpretation and reliability of this variable. It also includes descriptive statistics regarding the distribution of desired hours in the sample.

Importantly, I use a version of the French Labor Force Survey that provides access to the establishment identifier (the *SIRET*) for each worker's place of employment, as coded by Insee based on information from the worker's payslip. This feature, which to my knowledge is unique to the French version of the survey, is crucial to this study. The remainder of the paper considers only individuals for whom the *SIRET* information is available—82% of the original sample. This dataset enables the study of hours constraints observed at the worker level while accounting for firm-specific effects, a contribution that lies at the heart of this paper.

2.2 French Matched Employer-Employee Dataset (DADS)

The second source of data is the French matched employer-employee dataset *Base Tous Salariés* based on social security records (the *Déclarations Annuelles de Données Sociales / Déclaration Sociale Nominative*) and hereafter called *DADS*, notoriously used in Abowd et al. (1999). The dataset is constructed by Insee, based on administrative employer reports (mandatory for each employee subject to French payroll taxes) containing information on characteristics of the worker. In particular, it includes their income, paid hours worked, and length of employment spell. I use the *Fichiers Postes* version of the DADS, an exhaustive version that covers all jobs in the entire salaried workforce in each calendar year. The chaining procedure described by Godechot et al. (2023) is then used to build a quasi-exhaustive DADS panel dataset (DADS panel) over the period between 2003 and 2023, which enables the observation of employer-to-employer transitions for almost the entire workforce.

Using employer-reported paid hours worked as a measure of actual hours worked raises methodological concerns. Paid hours, as reported in the DADS, include all remunerated periods, i.e. not only regular working weeks but also paid leave. Hence, these hours tend to reflect contract hours and are uncertain to capture small adjustments. Appendix B3 assesses the quality of hours worked data by reproducing the approach of Lachowska et al. (2022) on Washington state administrative data, augmented with features specific to French labor regulations and data[4]. The implemented tests suggest that the quality of the data is comparable to the findings of Lachowska et al. (2022). As expected, paid hours tend to be quite concentrated around the reference duration (about 30% of the population works 35 hours per week) but there remains substantial variation likely driven by part-time work and overtime hours.

A particular feature of French working time regulations requires special consideration. *Forfait jours* contracts, covering approximately 15% of the workforce in 2019, measure working time in annual days rather than weekly hours. Under this arrangement, employers are not required to monitor or report actual hours worked in DADS records[5]. Insee addresses this data gap by im-

[4]In particular, the linkage of EEC and DADS datasets allows me to compare employer-reported and employee-reported hours for the same worker. Such comparisons have already appeared in previous research by Frazis and Stewart (2010). This work yet stands out as I rely on a much larger sample and on an administrative source of information on the employer's side.

[5]Breda et al. (2025) provides more background on this type of contracts and addresses the implications of workers' misperceptions about them on working conditions.

puting standardized annual hours (typically 1,820 or 2,200 hours depending on the year) of these workers, identifiable through the UNITMESUREREF variable since 2017. Given that these imputed values do not reflect actual working time and would introduce systematic measurement error into the analysis, workers in occupations with a large share of *forfait jours* contracts are excluded from the sample throughout most of the paper, with exclusions explicitly noted.

2.3 EEC × DADS Sample

Finally, the EEC and DADS datasets are linked together to build a unique new data set. Given the quasi-exhaustive nature of the DADS data on employment spells, most individuals surveyed in the EEC should appear in the DADS. In addition, workers should be identifiable based on information on age, sex, occupation, part-time/full-time work, birth department, birth month (only between 2009 and 2012), residence municipality, and crucially, establishment ID, which is supposedly consistent across sources. This information is thus mobilized to build a correspondence table between individual identifiers of both datasets. The procedure follows a "1-to-1"[6] matching approach on common variables, i.e. workers surveyed in the EEC are identified in the administrative records based on precise identical information across sources. This linkage is made possible by the presence in the EEC of the worker's establishment's ID (the *SIRET*). Importantly, the method used here relies on fuzzy matching, and thus can theoretically lead to errors in ID linkage. However, I reckon that the high precision of variables used and the conservative decision to remove all "1-to-many"[6] matches ensure a reliable linked dataset. The linkage is performed for every year between 2003 and 2023, keeping all quarterly information from the EEC and yearly information on all employment spells from the DADS. Appendix B4 details the entire matching procedure.

The operation yields a sample of 435,472 perfectly matched individuals between 2003 and 2023, a coverage of 67% of the EEC sample of employees[7] on this period. Cases where individuals cannot be matched across sources occur for three main reasons: (a) the establishment's ID is missing or incorrectly reported by the worker, (b) individuals are dropped during the cleaning process of the DADS as their information on hours or earnings is missing, (c) multiple workers cannot be distinguished based on the matching variables. The quarterly nature of the EEC and the link-

[6] I refer to a "1-to-1" match in this context to describe a situation where exactly one worker in the DADS dataset corresponds to exactly one worker in the EEC dataset based on identical values for the specified matching variables. Likewise, a "1-to-many" match depicts a situation where multiple workers in the DADS dataset corresponds to a unique worker in the EEC.

[7] After removing observations with missing number of hours worked or missing establishment's ID.

age of all DADS employment spells (including secondary jobs) over the period imply multiple observations per worker and year, hence generating a sample of 1,695,359 observations. This sample, hereafter denoted as the EEC-DADS sample, shows reasonably representative as described by summary statistics in Table A1. The most striking disparity with respect to the original EEC sample is the sizable under-representation of constrained part-time workers (representing 26% of part-time workers in the EEC-DADS sample against 34% in the original). This likely occurs because this population tends to hold more precarious positions with lower compliance on administrative duties, thus affecting the reliability of their information in both sources. As a result, the hours constraints that affect the part-time population in the EEC-DADS sample should reflect more stable and structural constraints than those in the original EEC sample. This is consistent with validity checks in the data: part-time workers who wish to increase their hours hold a permanent job more frequently (72% against 60% in the original sample) and have more experience in their current firm (76% have more than 1 year against 70% in the original sample).

92% of the workers in the EEC-DADS sample are then connected, using their yearly DADS identifier, to the previously chained DADS panel between 2003 and 2023. This dataset is denoted as the *EEC-DADS Panel*. As discussed in Godechot et al. (2023), the DADS panel is not fully exhaustive, which explains why some workers of the EEC-DADS sample cannot be recovered. The EEC-DADS Panel combines for each individual EEC-based information over 6 quarters of observation, hereafter the *EEC period*, and DADS-based information over the period of appearance in the panel. In other words, it contains information on individual preferences in terms of hours over a short period of time and on their employment history over a long period. The particular structure of this dataset is illustrated in Figure A1. The EEC-DADS panel gathers information on 399,553 individuals appearing 10 years on average in the panel, sometimes with multiple spells of employment over one year, resulting in a total of 9,734,018 observations.

This unique dataset paves the way for new empirical work on the topic of hours constraints by combining a self-reported measure from the Labor Force Survey with the panel dimension and reliability of administrative employer-employee datasets. Beyond this study, this dataset has potential applications across a wide range of research purposes, as the Labor Force Survey includes extensive information on various topics.

3 Employment Structure of Constrained Workers

This section provides new empirical evidence on the topic of hours constraints by exploiting an individual survey-based measure linked with employer information. Section 3.1 presents the main characteristics of workers who report being constrained in their hours. Section 3.2 quantifies the role of firm effects in shaping hours constraints and studies whether employer policies on hours can explain the presence of constrained workers. Section 3.3 targets the hours gaps that can occur between similar workers in the same firm and investigates potential mechanisms related to worker features.

3.1 Descriptive Statistics

This section examines the characteristics of workers who report ideal hours above their current level. The goal is to understand what types of workers express these preferences. This descriptive analysis will help interpret the main results presented later in the paper.

As presented in Section 2, three groups of workers are distinguished based on their answer to questions relevant to hours constraints in the Labor Force Survey: workers *constrained from above* who report that they ideally want to work more hours at their given wage rate, workers *constrained from below* who report that they ideally want to work less hours at their given wage rate and *unconstrained* workers who report no will to work different hours at their given wage rate. The defined groups respectively represent 19%, 2.5% and 78% of the Labor Force Survey sample between 2003 and 2023. This indicates that nearly one out of five salaried workers is constrained from above, while the share of workers constrained from below is minimal[8]. For this reason, the term "constrained" is used in the rest of the paper to refer to the constrained-from-above situation. Part-time workers are largely over-represented in the constrained from above population: 34% of part-time workers report that they would ideally increase their hours, as opposed to 17% in the full-time sample (see Table A1). About 70% of these constrained workers are *involuntary part-time* workers[9], i.e. they would ideally work as full-time employees, as derived from their desired hours. The sample consists of 112,523 part-time workers and 512,944 full-time workers.

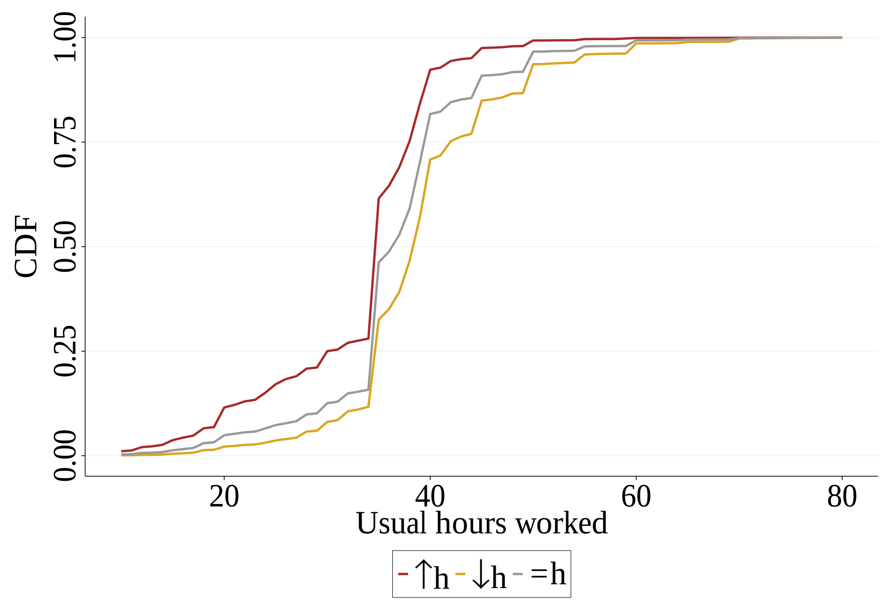
[8]This stands in sharp contrast with the prevalence of overwork in the German case, as documented by Jarosch et al. (2025). Interestingly, the distributions of desired hours are similar across countries but actual hours are higher in Germany, hence the difference in the direction of constraints.

[9]The term *underemployed* is also used in another literature (see e.g. Bell and Blanchflower (2021)) to refer to the same situation.

The sample has been restricted to salaried workers with non-missing hours worked and an hourly wage between 0.8 and 1000 times the hourly minimum wage.

Figure 1 displays the cumulative distribution functions of usual hours worked by groups of workers' preferences. The figure reveals a clear pattern: workers who prefer to increase their hours (red curve) work systematically fewer hours than those who are satisfied with their current hours (gray curve) or prefer to decrease them (yellow curve). The distribution of hours for constrained-from-above workers is strongly left-shifted, with a steeper rise in the CDF at lower values of usual hours worked. This indicates that their desire to work more stems directly from working fewer hours than other workers. While all three groups eventually converge around standard full-time hours, the initial divergence demonstrates that hours constraints are closely tied to actual hours worked, with those wanting more hours concentrated at lower values of the hours distribution.

Figure 1: Hours Worked by Group of Workers' Preferences

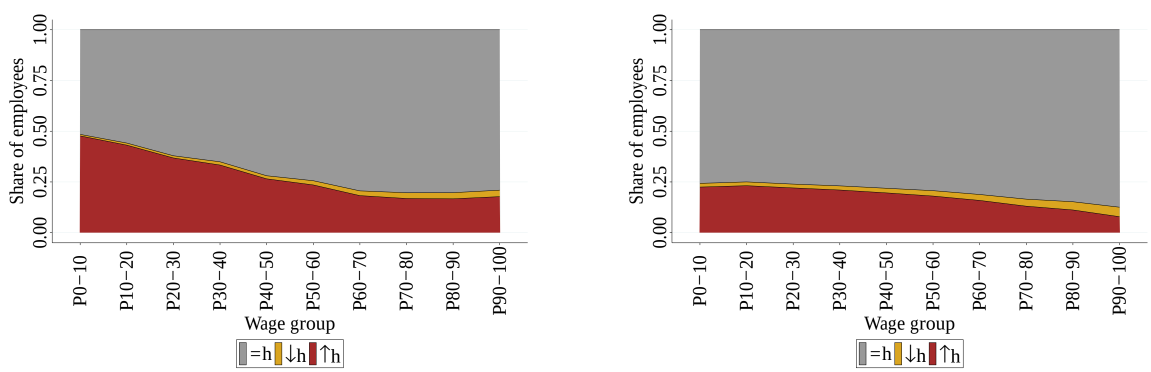


Note: The figure shows the cumulative distribution functions of usual hours worked by group of workers' preferences based on Labor Force Surveys pooled between 2003 and 2023. The sample consists of 625,467 salaried workers. The sample has been restricted to salaried workers with non-missing hours worked and an hourly wage between 0.8 and 1000 times the hourly minimum wage. Three groups are considered based on their answers to the following questions in the surveys: *"do you ideally want to work* [more/less] *hours in your job with a corresponding income variation?"*. "↑ h" workers report that they ideally want to work more hours ; "↓ h" workers report that they ideally want to work less hours ; "= h" workers answer no to both questions.

Figures 2a and 2b illustrate how the shares of constrained workers vary in the (hourly) wage distribution, separately for part-time and full-time workers. Unsurprisingly, preferences for a higher number of hours are regressive in wages. A simple interpretation of the pattern is that some workers aim to increase their earnings through hours worked to compensate for low wages (consistently with Figure B1b), i.e. the ”cross-sectional income effect” dominates. Likewise, the probability to be constrained from below is positively correlated with wages, although it remains marginal even at the top of the wage distribution. The relation between worker preferences in hours and wages well summarizes the profile of each group and Table A3 presents further details about their composition. Determinants of being constrained from above include being young, low-skilled, born outside of France, employed in a private sector firm, and in a non-permanent contract. As noted earlier, the constrained-from-above group has many more part-time workers, which lowers their average hours. But even when the sample is restricted to full-time workers, this group still works significantly fewer hours than the other groups. This shows that their desire to work more is driven by working shorter hours than most workers.

Figure 2: Workers’ Preferences in Hours in the Wage Distribution

(a) Part-Time (b) Full-Time



Note: The figures show the distributions of workers’ preferences based on Labor Force Surveys pooled between 2003 and 2023. The sample consists of 112,523 part-time workers and 512,944 full-time workers. The sample has been restricted to salaried workers with non-missing hours worked and an hourly wage between 0.8 and 1000 times the hourly minimum wage. Three groups are considered based on their answers to the following questions in the surveys: *”do you ideally want to work* [more/less] *hours in your job with a corresponding income variation?”*. ”↑ h” workers report that they ideally want to work more hours ; ”↓ h” workers report that they ideally want to work less hours ; ”= h” workers answer no to both questions. Wage groups, based on wage deciles, are defined within year and employment status (part-time/full-time).

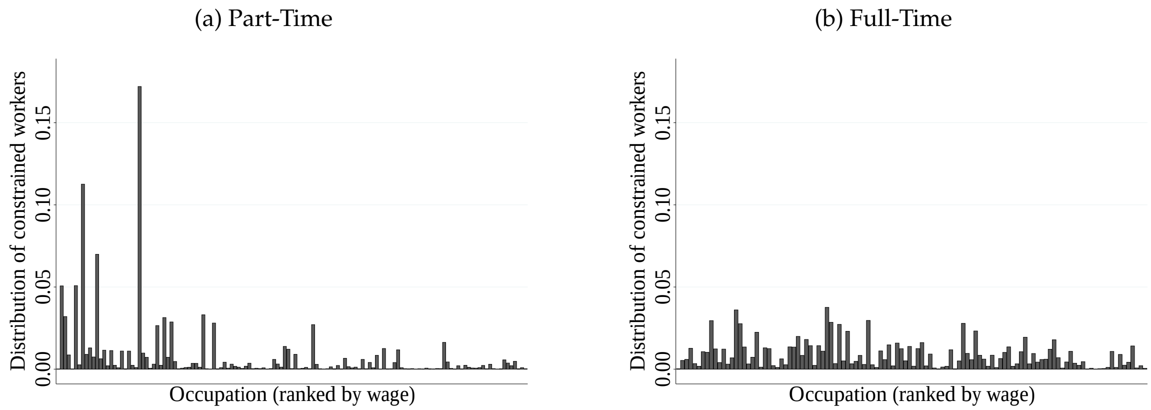
To end this section, I focus on the role of occupational sorting in hours constraints. Prior research (Altonji and Paxson, 1986) has often considered that working hours are largely occupation-specific. For instance, assembly line workers exhibit strong uniformity in hours worked due to standardized shift schedules (such as 8-hour shifts) common in manufacturing contexts. Therefore, it seems reasonable that some workers face constraints on their hours because their jobs structurally involve shorter working periods. To test this hypothesis, I leverage information on hours constraints from the EEC at the occupation level. Figures 3a and 3b plot the distribution of part-time workers who wish to increase their hours by occupation, respectively for part-time and full-time. Occupations correspond to the 3-digit level in the PCS classification (110 levels) and are ranked by average wage, computed separately for part-time and full-time workers using DADS data.

Figure 3a shows that constrained part-time workers are heavily concentrated in a limited number of occupations that are notorious for their low wages and high proportion of part-time employment. Four occupation groups—childcare workers (the highest bar), cleaners (either in the public or the private sector), sales assistants, waiters—gather half of part-time workers who are constrained from above (as well as involuntary part-time workers) while representing about 30% of part-time workers. Figure A2a plots the same distribution relative to the distribution of all part-time workers and shows a clear regressive pattern: workers who wish to work more are overrepresented in low-wage jobs. The magnitude of the over-representation suggests that occupational sorting is an important feature of this type of constraints.

In contrast, Figure 3b shows a far more even distribution of constrained workers across occupations in the full-time group. 23 occupations, over 110, account for half of constrained full-time workers. There is no notable concentration in low-wage jobs, as confirmed by the relative distribution in Figure A2b. While some low-wage occupations—such as warehouse workers, security guards, and retail workers—are somewhat overrepresented, the wage gradient is overall flat. Note that both figures are extremely similar if hours, instead of wages, are used to rank occupations, since there is a strong positive correlation ($R^2 = 0.57$) between both variables at the occupation-level. The main idea here is that the mechanisms driving hours constraints differ fundamentally between part-time and full-time employment.

This strong concentration among part-time workers does not reflect structural barriers at the occupation level, as full-time work is common or even predominant in these occupations. Occupational sorting therefore cannot be explained by uniformity in hours within jobs, as anticipated in earlier work. Instead, other sources of heterogeneity likely explain why some workers cannot secure full-time jobs. For instance, constrained part-time workers differ in a number of characteristics from full-time workers in their given occupation: they are less experienced, more likely to

Figure 3: Occupational Sorting



Note: The figures show the distributions of constrained (from above) workers across occupations by working time status. Data is based on Labor Force Surveys pooled between 2003 and 2023. Each bar corresponds to an occupation (ranked by wage) at the 3-digit level in the PCS classification (110 levels). The y-axis indicates the proportion of the population constrained from above that works in a given occupation. An individual is constrained from above if he or she answers yes to the question: *"do you ideally want to work more hours in your job with a corresponding income variation?"* in the Labor Force Survey.

hold temporary contracts and more exposed to discrimination (their probability of being woman or born abroad is higher). In the next section, I examine whether firm sorting may explain some part of the concentration of constrained workers.

3.2 Firm Sorting

This section studies the role of firm sorting in the phenomenon of hours constraints. I take advantage of the presence of establishments' IDs in the French Labor Force Survey to examine the distribution of constrained workers across firms. This approach complements recent work by Labanca and Pozzoli (2023) on the role of firms in hours constraints using direct survey-based evidence of these constraints. This measure also enables to connect worker hour preferences with employer hour policies, a relation at the heart of Lachowska et al. (2023)'s work, by which this section is largely inspired. The section further provides evidence on the interaction between firm effects and occupational effects, i.e. the extent to which firm heterogeneity explains hour variation within occupations.

AKM Estimation. As in Babet and Chabaud (2024), I use a chained DADS panel between 2005 and 2019, quasi-exhaustive of the French salaried workforce, and apply several restrictions to the sample[10]. Hours worked are annualized paid hours, and wages correspond to real net hourly wages. The sample is also restricted to the largest weakly connected set of firms, as is common in this literature (Card et al., 2013). The estimation sample contains 29,824,763 workers and 1,318,726 firms. The following model is fitted:

$$y_{it} = \phi_i + \psi_{j(i,t)} + X_{it}\beta + u_{it}$$

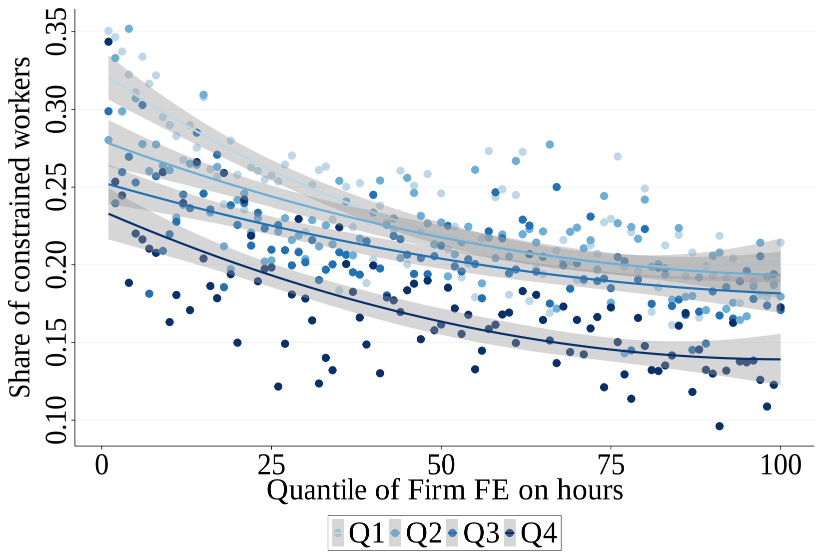
with y_{it} the logarithm of the outcome (either hours or wages) of worker i in year t. ϕ_i is the fixed effect of worker i, and $\psi_{j(i,t)}$ is the fixed effect of firm $j(i,t)$, the employer of worker i during year t. ψ_j is therefore a measure of firm j's premium in the corresponding outcome, i.e. the component of hours or wages that is due to the general policy of the firm. Time-varying covariates X_{it} are limited to fixed effects for years and age as a cubic polynomial. u_{it} is the idiosyncratic error term. This model can be used to decompose the variance in hours and wages into components associated with worker and firm heterogeneity and sorting, as done in Babet and Chabaud (2024) with the same data. The goal here is rather to use the estimated employer effects for their interpretative value.

Job Ladder. Employer effects are split into percentiles and each combination of hour-effect percentile and wage-effect quartile is associated with the share of workers within the cell who report constraints from above. Thus, each combination characterizes groups of firms with similar policies in hours and wages. Figure 4 shows a distinctive pattern of worker preferences related to firm policies. The share of constrained workers is at its highest level in firms with low-hour and low-wage (Q1) policies, and decreases as the group of firms is associated with higher levels of hours or wages. This result is consistent with the idea of a job ladder, previously introduced in Lachowska et al. (2023) as a mechanism of hours constraints, i.e. a hierarchical ranking of employers based on the desirability of their jobs. In other words, most workers want to work for the same firms, those with high employer effects, but limited availability of those jobs implies that some of them end up as constrained in lower quality jobs. By combining individual-level survey information on constraints with firm effects on hours, this figure provides to my knowledge the most prominent

[10]Workers aged between 15 and 64, in ordinary jobs of more than 120 hours and 60 days, with hourly wage greater than 0.8 minimum wage and smaller than 2,000 minimum wages. I also keep only one observation per person-year so I take the annual dominant employer of the worker (defined as the employer from which the worker earns the most during the year). Occupations with more than 20% of forfait jours workers in the EEC between 2013 and 2023 are excluded from the sample.

empirical evidence for this mechanism in the case of hours constraints.

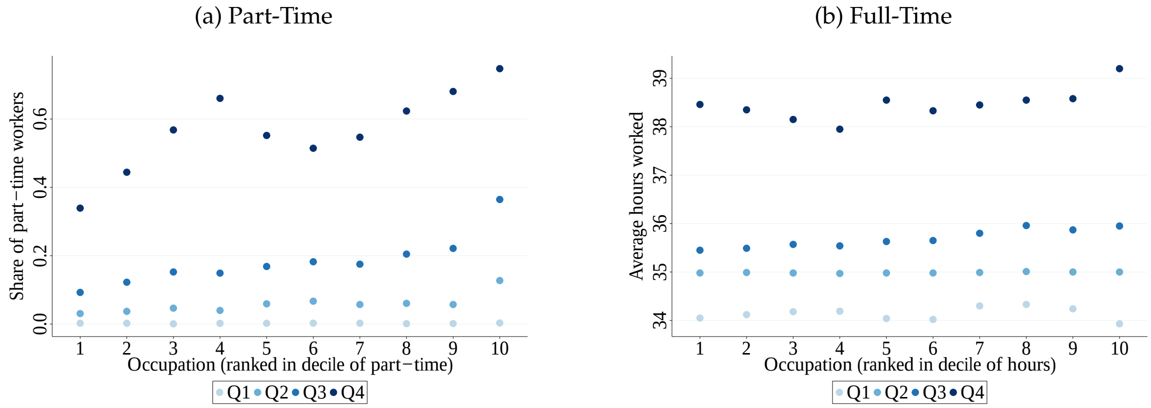
Figure 4: Hours Constraints and Firm Policies



Note: This figure represents the relationship between hours constraints and AKM firm effects on hours and wages. The x-axis represents the percentile of firm fixed effect on hours, while the y-axis shows the share of workers constrained in their hours. The four groups (Q1-Q4) represent different firm wage-effect quartiles, with darker points indicating higher wage quartiles. All firm effects are estimated through an AKM decomposition. The data used is a panel based on chained DADS yearly files between 2003 and 2023. See the text for details. Hours worked are paid hours recomputed as full-year equivalent. Shaded areas correspond to 95% heteroskedasticity-robust confidence intervals.

Firm Sorting and Occupational Sorting. To explore whether firm effects are driven by concentration in occupations with short or long hours, I examine the interaction between firm and occupational sorting. Figures 5a and 5b plot average hours by groups of firms and occupations, respectively for part-time and full-time workers. where Firms are divided into quartiles based on their share of part-time workers (a) or average hours worked (b), and occupations are grouped into deciles using the same respective measures. Each point in the figures represents the average hours worked for a specific firm-occupation group. For full-time workers (b), the profiles across occupation deciles are relatively flat within each firm quartile, reflecting limited variation in hours across occupations within a given firm. This means that firm sorting accounts for most of the variation in hours across workers. For part-time workers, profiles depict an upward slope in firms that are intensive in part-time work. This indicates that firms do not equally rely on part-time work for different occupations. Conversely, a large variation in shares of part-time work exists within decile of occupations, which suggests that firms differ in their use of part-time work in a given occupation. Hence, involuntary part-time work is likely driven by a combination of firm and occupational effects.

Figure 5: Firm Heterogeneity in Occupation Effects



Note: This figure represents the average hours worked by group of firm and occupation. Data is based on DADS yearly datasets pooled between 2009 and 2023. The sample is restricted to full-time employees. Hours worked are paid hours recomputed as full-year equivalent. Occupations correspond to the 3-digit level in the PCS classification (110 levels). Deciles of hours worked are derived from average (paid) hours worked per week computed at the occupation level. For example, the first group on the x-axis corresponds to the 10% of workers who work in occupations with the lowest average hours. Firms are ranked by average paid hours worked of their employees and divided into quartiles.

3.3 Within-Firm Heterogeneity in Hours

Previous results highlight the role played by occupational and employer effects in hours constraints. However, there remains non-negligible variation in hours inside of firms, including between constrained and unconstrained workers. Table A4 reports the difference in hours between both types of workers using varying sets of controls and fixed effects. Both measures of hours, paid and reported, are considered using the common EEC-DADS sample. For all specifications, the sample is restricted to workplaces with at least one constrained and one unconstrained worker in order to allow for variation after adding a workplace fixed effect. Constrained workers consistently work fewer hours than unconstrained workers under both definitions of hours, even when controlling for occupation and workplace fixed effects. This result is surprising to some extent, as one could expect a large coordination in hours within workplaces, motivated by production rigidities and the practice of collective hours schedules (Kahn and Lang, 2001). This section develops a complementary approach to explain why workers doing the same job in the same firm may work a different number of hours.

The goal of the section is to compare the characteristics of constrained workers with those of their coworkers who work more hours. First, constrained workers are identified in the EEC-DADS sample by the triplet year $\times$ workplace $\times$ occupation at the 3-digit level in the PCS classification (110 levels). This degree of precision ensures comparisons among similar workers. I then split the sample into part-time and full-time subsamples and use the exhaustive DADS yearly datasets to collect information on all workers sharing the same triplet as a constrained worker. The data include detailed characteristics such as earnings, gender, age, country of birth (derived from birth department), distance to workplace (based on residence and workplace municipalities), and paid hours worked.

The analysis is restricted to 2009-2023 for two reasons. First, the occupation variable in the DADS (PCS) is only consistently coded at the 3-digit level from 2009 onward. Second, I use the DADS panel to calculate each worker's tenure in their current firm. Since the panel extends back to 2003, I restrict the data to 2009 and winsorize tenure values above five years.

This approach yields information on the characteristics of at least one constrained worker and nearly all their coworkers for a large number of jobs defined by the triplet year × workplace × occupation. Note that the methodology does not capture coworkers' preferences but instead provides a comprehensive view of the hours distribution surrounding constrained workers. The goal is to understand why some workers work more hours than a colleague who wishes to do so.

Rather than comparing constrained workers to all coworkers, I focus on those whose hours worked are arbitrarily close to the desired hours of constrained workers. For part-time workers, I restrict the sample to involuntary part-time workers and compare them to full-time coworkers in the same triplet. For full-time workers, I compare them to coworkers working at least one additional hour per week[11]. After removing observations with missing variables, I obtain a sample of 269,617 workers in 8,931 triplets for part-time and 336,966 workers in 16,636 triplets for full-time. This targeted approach isolates the observable characteristics that distinguish workers able to work longer hours from those unable to do so despite wanting to.

A key assumption is that constrained workers in the EEC-DADS sample are representative of the broader population of constrained workers in their triplet. To test the validity of this as-

[11]Estimates are very similar when using 3 or 5 additional hours as the threshold.

sumption, I examine triplets with at least one involuntary part-time worker and compare full-time coworkers from the full DADS with full-time workers from the EEC-DADS sample in the same triplet. If the assumption holds, these two groups should exhibit similar characteristics. Table A5 presents this falsification test. I find that women and workers over 45 are underrepresented in the EEC-DADS sample. This suggests that differences in these characteristics in the main analysis may be negatively biased and thus represent lower bounds of the true differences. Other coefficients are not significantly different from zero, supporting the validity of the approach.

Table 1 reports the difference in characteristics between constrained workers and their comparison group. Panels A and B respectively show results for part-time and full-time constrained workers. Observables include age (in five categories), gender, tenure in the firm, being born abroad, and distance to workplace (in kilometers). Each coefficient is estimated in a separate regression controlling for all other observables. The coefficient on wages is only incorporated for full-time workers, as comparing hourly wages across working time status is not meaningful. I find distinct patterns by working time status, reinforcing the idea that hours constraints are driven by different mechanisms in part-time and full-time work.

In Panel A, involuntary part-time workers differ from their full-time coworkers in several dimensions. Gender plays a significant role: being constrained is associated with a 11.4 percentage point higher probability to be a woman. Given the falsification test results showing that women are underrepresented in the EEC-DADS sample for these triplets, this estimate represents a lower bound, suggesting the true correlation between gender and hours constraints is even stronger. Experience also matters substantially at the workplace level. Involuntary part-time workers have on average 0.2 fewer years of tenure in their current firm compared to full-time coworkers in the same triplet[12]. Age shows a negative association with constraints for workers aged 35 and above, though this result should be interpreted cautiously given the underrepresentation of older workers in the EEC-DADS sample (see Table A5). Finally, involuntary part-time workers are more likely to be born abroad and live closer to their workplace, although the correlation is weak in both cases.

In Panel B, gender remains a significant determinant, though with a much smaller estimate. Unlike in the part-time case, experience shows no association with hours constraints, and being

[12]Note that the experience is capped at 5 years.

foreign-born plays a negligible role. Constrained full-time workers also tend to live closer to their workplace, by an average of 5 kilometers. An important finding is that constrained workers and their coworkers with longer hours earn virtually identical wages, once other characteristics are accounted for. This suggests that workers who wish to increase hours in their given job are not compensated through higher wages.

Table 1: Within-Firm Determinants of Hours Constraints

Dependent Variable:	Age					Female	Experience	Foreigner	Distance	Wages
	15-24	25-34	35-44	45-54	55+					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Part-Time										
Involuntary Part-Time	-0.001	-0.011	0.028***	0.002	-0.018***	0.114***	-0.208***	0.008*	-1.612*	-
	(0.004)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.022)	(0.004)	(0.721)	-
Observations	269,617	269,617	269,617	269,617	269,617	269,617	269,617	269,617	269,617	-
Triplets	8,931	8,931	8,931	8,931	8,931	8,931	8,931	8,931	8,931	-
Adj. R^2	0.24	0.14	0.08	0.12	0.14	0.35	0.47	0.39	0.46	-
Panel B: Full-Time										
Constrained	-0.005*	0.028***	0.034***	-0.008*	-0.049***	0.012***	0.285***	-0.001	-5.031***	-0.002
	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.014)	(0.003)	(0.571)	(0.001)
Observations	336,966	336,966	336,966	336,966	336,966	336,966	336,966	336,966	336,966	336,966
Triplets	16,636	16,636	16,636	16,636	16,636	16,636	16,636	16,636	16,636	16,636
Adj. R^2	0.22	0.17	0.09	0.13	0.15	0.46	0.47	0.31	0.54	0.68
Controls and Fixed Effects										
Year × Workplace × Occupation	X	X	X	X	X	X	X	X	X	X
Age (Polynomial)						X	X	X	X	X
Female	X	X	X	X	X		X	X	X	X
Experience	X	X	X	X	X	X		X	X	X
Foreigner	X	X	X	X	X	X	X		X	X
Distance	X	X	X	X	X	X	X	X		X

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents estimates from OLS regressions of differences in individual characteristics between constrained workers and their coworkers with more hours. Constrained workers are identified by a year × workplace × occupation triplet in the EEC-DADS sample and information is collected from the DADS for all employees in these ”clusters”. See the text for more details. Panel A compares involuntary part-time workers with their full-time coworkers. Panel B compares full-time workers who report constraints with their coworkers with at least one additional hour worked per week. Occupations correspond to the 3-digit level in the PCS classification (110 levels). Occupations eligible to forfait jours contracts are removed from the sample. Age is split in 5 categories to account for non-linearities. Experience corresponds to the number of years employed in current firm and is winsorized at 5 years due to data limitations. Foreigner is a dummy variable equal to 1 if the individual is born abroad. Distance corresponds to the distance to commute (in kilometers). Standard errors are clustered at the year × workplace × occupation level and reported in parentheses.

4 Labor Market Transitions of Constrained Workers

This section provides first evidence on the evolution of constrained workers in the labor market. The depiction of constraints as partly driven by job or firm sorting suggests that workers would have to switch firms to align with their hour preferences. A central analytical focus is to understand to what extent constrained workers can improve their situation through mobility. Section 4.1 studies the relation of hours constraints to worker mobility and presents descriptive evidence on the evolution of hours and earnings. Section 4.2 introduces an event-study framework to estimate differential changes in hours and earnings experienced by constrained workers. Section 4.3 explores the types of mobility by which constrained workers adjust their hours. Section 4.4 examines the heterogeneity behind the main effects and discusses the ability for different workers to relax their constraints. Section 4.5 provides robustness checks to the main estimates.

The entire dynamic analysis relies on the EEC-DADS sample introduced in Section 2.3. Similar restrictions to Babet and Chabaud (2024) are applied to the sample[13] and their definition of voluntary moves is used for robustness checks. Additionally, the period of activity is limited to the continuous sequence of years around the EEC period and to individuals who appear both before and after it. After restrictions, the sample is composed of 157,716 workers. 17.5% are labeled as constrained in the last quarter of their EEC period. This measure of hours constraints is used in the rest of the section and the year of the last EEC quarter serves as the reference year ($t = 0$). Workers appear on average 13.5 years in the panel (the median is 14). In short, the EEC-DADS panel maintains the same structure as the DADS panel, supplemented with additional information from the last year of EEC survey administration.

4.1 Worker Mobility

First, the focus is on the relation of hours constraints to mobility. In this first part of the section, worker mobility is measured by a dummy variable equal to 1 if the individual switches employers at least once between years 1 and 3 after the EEC period. The reference EEC employer is adjusted to the last employer reported in the EEC, thus counting any subsequent employer change in year $t = 0$ as a transition in $t = 1$. The three-year observation window is motivated by the persistence

[13] Workers aged between 15 and 64, stable working contract (*CDD* or *CDI*), annual hours above 120, hourly wage between 0.8 and 2000 minimum wages, and focus on primary employment (defined as the spell that induces highest earnings).

of hours preferences over a short period of time after the EEC[14]. For this part only, the sample is also restricted to employers with at least 2 workers in the sample during their EEC period to allow for the inclusion of an EEC employer fixed effect. The sample used covers 94,503 workers employed in 19,251 firms during their EEC period.

Evidence demonstrates that constrained workers exhibit greater mobility, even in similar employment contexts. Table 2 indicates that constrained workers have a 3.7 pp higher probability of changing employers compared to unconstrained workers over the 3-year span. The coefficient is much higher for part-time (β = 0.102***) than full-time workers (β = 0.028***). The magnitude of the coefficient is cut by two when demographic and occupational controls are introduced, but it remains strongly significant. Constrained workers show a 1.2 pp, 7% of the baseline, higher probability of changing firms roughly unchanged after the inclusion of employer fixed effects.

Table 2: Hours Constraints and Worker Mobility

Dependent Variables:	*Move in Years 1-3*			
	(1)	(2)	(3)	(4)
Constrained	0.037***	0.012***	0.018***	0.012**
	(0.003)	(0.003)	(0.003)	(0.004)
Controls and Fixed-effects				
EEC Year	X	X	X	X
Part-/Full-Time (EEC Period)	X	X	X	X
Demographics (EEC Period)		X	X	X
Occupation (EEC Period)			X	X
Employer (EEC Period)				X
Baseline	0.16	0.16	0.16	0.16
Share of Constrained	0.17	0.17	0.17	0.17
Observations	94,503	94,503	94,343	94,343
Adj. R^2	0.01	0.04	0.04	0.36

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents estimates of the relationship between hours constraints and job mobility. The data used is the EEC-DADS sample (see Section 2.3 for details). The sample is restricted to firms with at least 2 workers. The dependent variable is a dummy variable equal to 1 if the individual switches employers between 1 and 3 years after the EEC period. An individual is constrained (from above) if he or she answers yes to the question: *"do you ideally want to work more hours in your job with a corresponding income variation?"* in the Labor Force Survey. Demographics include age, gender and county of residence. Occupations correspond to the 3-digit level in the PCS classification (110 levels). Standard errors are heteroskedasticity-robust and reported in parentheses.

[14]In Appendix B2, I discuss the persistence of hours preferences during the EEC period and find non-negligible instability as only 63% of workers who are constrained in their last EEC quarter are also constrained in their first one. This potential threat is addressed in Section 4.5 by using a more restrictive definition of stable constrained workers. Also note that restricting the window to 2 years after the EEC period barely changes the estimates.

Do constrained workers who switch employers increase their hours? Figure 6 illustrates the trajectories of weekly paid hours worked for four distinct groups: constrained workers (*constrained-movers*) and unconstrained workers (*unconstrained-movers*) who switch employers at least once between periods 1 and 3, and their equivalent who remain with the same employer (*constrained-stayers* and *unconstrained-stayers*)[15].

Constrained workers who switch employers experience a substantial increase in their working hours through their mobility. Their upward trajectory contrasts with constrained workers who stay at their original employer, whose hours remain relatively flat and only increase through occupational mobility. Unconstrained workers work more hours regardless of whether they change jobs or not and maintain an overall stable level across the observation window. The gap in levels between both groups of constrained workers is mostly due to the higher proportion of part-time workers in the sample of movers.

Figure 6 supports the argument that hours constraints drive job mobility, as constrained workers who switch firms appear to increase their hours towards their desired level, while those who remain in the same firm show more stability. This stability suggests that workers classified as constrained have little influence over hours within their current firm, and must switch firms to adjust them. Figure A3 confirms that these hour trajectories translate to earnings, with constrained-movers showing a distinct jump in earnings immediately following the EEC period.

4.2 Event-Study Design

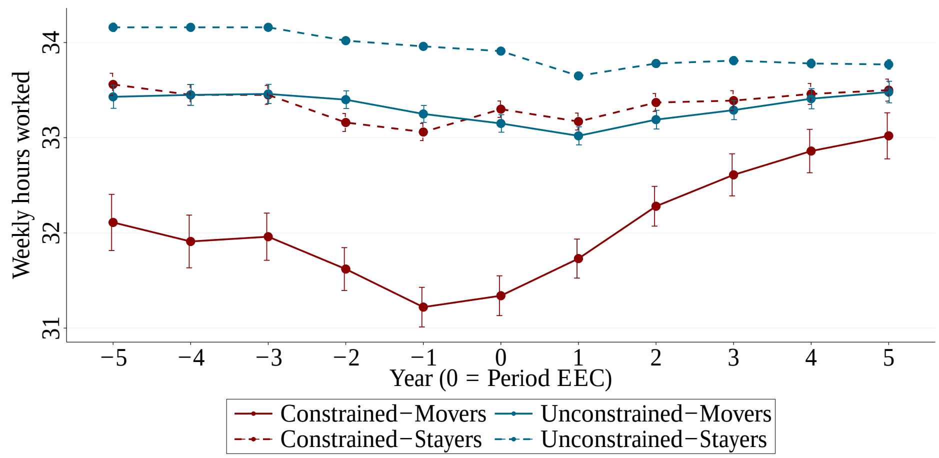
This section studies the evolution of constrained workers as compared to unconstrained workers in a more formalized approach. Given that constrained workers are mostly able to adjust their hours by switching firms, I estimate the differential effects associated with employer-to-employer mobility for both types of workers. I use an event-study design corresponding to the following equation:

$$y_{it} = \beta_1 \times S_{it} + \beta_2 \times S_{it} \times C_i + \alpha_i + \gamma_t + \varepsilon_{it} \tag{1}$$

The considered outcomes y_{it} are hours worked, hourly wages, and earnings (in logs). S_{it} is a dummy variable equal to 1 if the individual i is a "*mover*" in year t, where t must be between 1

[15]The sample divides across the four groups as follows: 5.2%, 16.0%, 14.3%, and 64.5%.

Figure 6: Evolution of Hours in the EEC-DADS Panel



Note: This figure represents the evolution of weekly hours across employer-to-employer transitions for different worker groups. The x-axis shows years relative to the EEC period, while the y-axis displays average weekly paid hours worked from the DADS. The data used is the EEC-DADS sample (see Section 2.3 for details). Four distinct groups are tracked: constrained-movers (solid red line), unconstrained-movers (solid blue line), constrained-stayers (dashed red line), and unconstrained-stayers (dashed blue line). Workers are classified as constrained or unconstrained based on their reported hour preferences, and as movers or stayers based on whether they switch employers during years 1 to 3 after the observation period. Error bars correspond to 95% heteroskedasticity-robust confidence intervals.

and 3 years after the EEC period. This restriction on considered moves favors their consistency with hours preferences reported in the EEC[16]. C_i is a dummy variable equal to 1 if the individual i is constrained in the last year of the EEC period. α_i and γ_t are respectively worker-specific and year-specific fixed effects. β_1 captures the effect on the outcome associated with employer-to-employer moves. β_2 measures the differential effect for constrained workers. Worker fixed effects are included to control for time invariant unobserved heterogeneity. The sample gather all moves that occur between the EEC period and up to 3 years after it. This corresponds to 32,269 employer-to-employer moves over a sample of 157,716 workers and 543,679 observations, with constrained workers covering 20% of moves.

Event-study designs are a widely used method for estimating treatment effects. Their validity relies on two critical identifying assumptions: no-anticipation and parallel trends (Borusyak et al., 2024). The no-anticipation assumption requires that workers do not change their behavior before switching jobs, while the parallel trends assumption holds if workers who change employers or stay would have followed similar trajectories in outcome absent mobility. A common way to test the validity of the parallel trends assumption is to examine the similarities of treatment and control

[16]In addition, in the case where the individual experiences multiple transitions shortly after the EEC period, I only consider the first move as it is the one consistent with reported hours preferences.

groups in trend during the pre-event window. In this context, neither assumption is satisfied as both employer-to-employer moves and worker constraint status are likely endogenous to prior dynamics in working hours.

Figure A4a plots event-study coefficients associated with moves on hours worked following Callaway and Sant'Anna (2021)[17] and provides direct evidence of violations. The pre-event coefficients, though modest in size compared to the post-event ones, are significantly different from zero and show a notable decline in hours just before the move. This pre-move drop suggests that workers whose hours are decreasing are more likely to switch employers. Figure A4b show the equivalent coefficients for the interaction term by comparing constrained and unconstrained workers who switch firms. Both groups exhibit similar pre-trends in hours, suggesting that being constrained is not associated with different prior evolution of hours. Since the fundamental parallel trends assumption is violated in Figure A4a, the estimates cannot be interpreted as treatment effects. Here, I use the event-study framework as a descriptive tool, as it provides a clear and intuitive quantification of how working hours of constrained and unconstrained workers diverge around employment transitions.

Table 3 reports estimates of the coefficients in Equation 1. Coefficients are estimated separately by employment status (part-time or full-time) during the EEC period. The first row shows the effects associated with employer-to-employer moves for unconstrained workers. I find that switching firms is associated with a 2.4% increase in hours among part-time workers, driven by a 13 pp higher probability to move full-time, while it does not affect the evolution of hours in the full-time sample. All types of movers yet experience a relative decrease in wages, which leads to a reduction in earnings for full-time workers.

Negative wage effects associated with job mobility may appear as surprising, as they reflect that workers would voluntarily quit a job for another that pays less. This result is yet consistent with previous findings by Babet and Chabaud (2024), who study wage dynamics of individuals who switch employers using the same data. Their definition of voluntary employer-to-employer moves is yet more restrictive, as it considers only moves out of a permanent contract (*CDI*) that did not involve a significant unemployment spell within the move. The assumption that employer-to-employer moves are voluntary is essential to the interpretation of effects as aligned with a

[17] The control group is composed of non-movers, i.e. *never-treated* individuals.

revealed preference strategy. In Section 4.5, I re-estimate the coefficients using their definition and find significantly larger estimates on hours and earnings for both employment status.

Table 3: Event-Study Effects on Hours, Wages and Earnings

Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Mover	0.024***	-0.039***	-0.016	-0.002	-0.046***	-0.048***
	(0.009)	(0.004)	(0.009)	(0.002)	(0.001)	(0.002)
Mover × Constrained	0.063***	-0.009	0.055***	0.008*	0.004	0.012**
	(0.015)	(0.007)	(0.014)	(0.004)	(0.003)	(0.004)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline	25.4	13.8	18,341	34.6	16.5	29,595
Observations	60,413	60,413	60,413	483,266	483,266	483,266
Adj. R^2	0.78	0.89	0.88	0.60	0.93	0.90

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents estimates from event-study regressions specified in equation 1. The data used is the EEC-DADS sample between 2003 and 2023 (see Section 2.3 for details). The first three columns of the table correspond to estimates when restricting the sample to workers who primarily worked as part-time during the last year of their EEC period. The last three columns correspond to results in the equivalent full-time sample. The dependent variables are respectively the logs of weekly hours, hourly wages and net annual labor earnings from the DADS data. Hours are paid hours recomputed as full-year equivalent and divided by 52. Earnings are also recomputed as full-year equivalent based on the number of days worked over the year. "Mover" is a dummy variable equal to 1 if the worker's primary employer is different than the year before. The primary employer is defined as the one with highest annual earnings. In addition, moves used for the estimation must occur between 1 and 3 years after the EEC period. "Constrained" is a dummy variable equal to 1 if the worker is constrained (from above) in their hours in the last year of their EEC period. Worker fixed effects (Worker FE) control for time-invariant unobserved heterogeneity. Year fixed effects (Year FE) control for common time trends. Standard errors are heteroskedasticity-robust and reported in parentheses.

The second row reports differential effects of employer-to-employer mobility for constrained workers, the primary focus of this paper. The estimates show that mobility is associated with relative positive effects in hours and earnings for constrained. Constrained part-time workers who switch employers experience a 8.7% relative increase in hours, and a 17 pp higher probability to move full-time. Their earnings are 3.9% higher than constrained workers who do not move, hence employer-to-employer mobility is a more effective way for constrained workers to increase their revenues. Adjustments in hours and earnings are more limited for full-time workers. Constrained workers experience relative increases in hours and earnings as compared to unconstrained workers, but the combination of both coefficients still implies a 3.6% decrease in earnings for them.

Figure A5 explores heterogeneity in mobility effects across occupational groups, splitting the sample by workers' broad occupation during the EEC period based on the first digit of the PCS classification (4 levels). The large effects on hours among part-time workers are primarily driven by tertiary low and mid-skill occupations. Constrained workers in low-skill (non-manual) occupations experience an 11% increase in hours, significantly larger than the 4.5% increase for their unconstrained counterparts. This finding is particularly important as this group represents 55% of the sample of constrained part-time workers. Their hours adjustments translate into a 7% relative increase in earnings. For full-time workers, no occupation really stands out, although mid-skill workers tend to experience slightly larger hours adjustments.

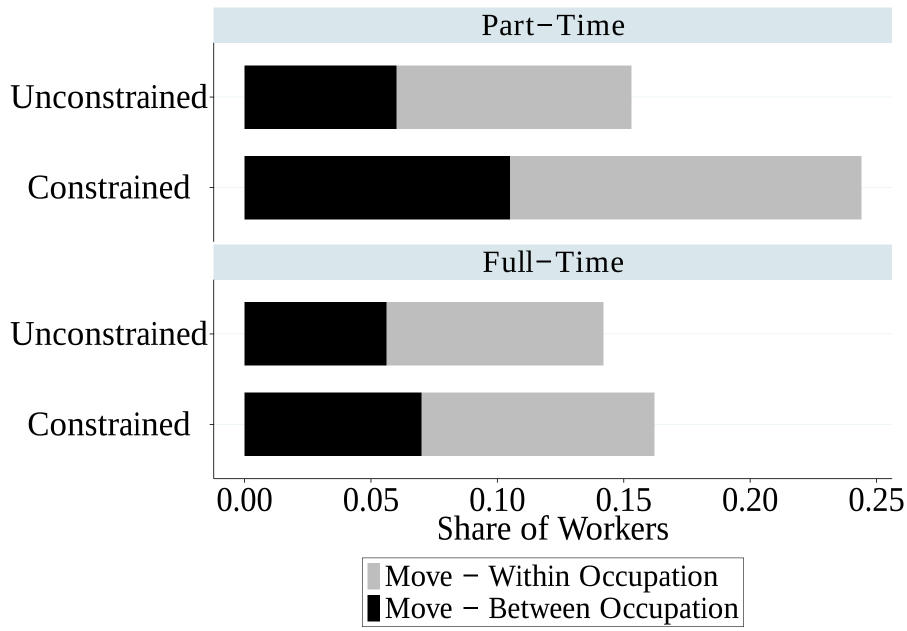
To summarize, the results reveal that switching employers is a particularly effective way for involuntary part-time workers to adjust their hours and boost their earnings. Conversely, full-time workers who report facing hours constraints move in a similar way than other full-time workers. This contrast suggests that part-time workers face tighter hours constraints in their jobs, i.e. their disutility from being underemployed is larger than it is for full-time workers. Another potential explanation lies in the difficulties for full-time workers to increase their hours as overtime hours are rarely advertised by employers.

4.3 Adjustment Mechanisms

The previous section showed that employer-to-employer mobility is the primary source of adjustment in hours and earnings. In this section, I examine how constrained workers increase their hours through different types of mobility, e.g. whether they remain in their current occupation or switch to a new one. By studying those mechanisms, I provide insights into the underlying structure of hours constraints in the labor market.

Types of Mobility. Figure 7 presents the distribution of employer-to-employer transitions for constrained and unconstrained workers by employment status. I classify movers into two categories based on their first move after the EEC period: those who remain in the same occupation (*within-occupation*) and those who switch to a new one (*between-occupation*). As already noted in Table 2, constrained workers exhibit a higher propensity to switch firms, especially for part-time workers. Conditional on moving constrained and unconstrained workers are relatively similar in their distribution across groups, e.g. 43% of constrained part-time movers experience a between-occupation move, against 39% for their unconstrained counterparts.

Figure 7: Types of Mobility



Note: This figure displays the distribution of job-to-job transitions by type of mobility for constrained and unconstrained workers, separately for part-time and full-time employees. The data used is the EEC-DADS sample (see Section 2.3 for details) and includes moves occurring between 1 and 3 years after the EEC period. When workers experience multiple transitions during this window, only the first is retained. Black bars represent within-occupation moves (workers who change employers while remaining in the same occupation), while gray bars represent between-occupation moves (workers who change both employer and occupation). The horizontal axis shows the share of workers in each category.

Effects by Type of Mobility. The focus on occupational mobility stems from findings in Section 3, which demonstrated that involuntary part-time workers are heavily concentrated in few occupations. This suggests that they need to switch occupations to substantially increase their hours. If this is true, between-occupation moves should generate larger hours increases than within-occupation moves. To test this, I re-estimate the coefficients from Equation 1 separately for workers who stay in their occupation versus those who switch, while still using non-movers as the comparison group.

Table 4 shows that employer-to-employer mobilities are consistent with previous findings on occupational sorting. For part-time workers, between-occupation moves lead to much larger hours increases than staying in the same occupation: 4.5% vs 1.1% for unconstrained workers, and 11.1% vs 6.5% for constrained workers. This occurs mainly because workers who switch occupations are more likely to transition to full-time work (15 pp more for unconstrained workers and 11 pp more for constrained workers). Hence, between-occupation moves yield significant earnings gains while within-occupation moves do not. The picture is different for full-time workers. The estimates of the interaction term from Panel A are close to 0, i.e. moves within the same occupation produce similar outcomes for both constrained and unconstrained workers. For between-occupation moves, constrained workers tend to increase their hours and earnings in relative terms, but it comes as a result of large declines across unconstrained workers' moves. The combination of the two coefficients implies a slight increase in hours that does not offset the large negative change in wages.

Table 4: Event-Study Effects By Occupational Mobility

Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Panel A: Within-Occupation						
Mover	0.011	-0.025***	-0.013	0.004	-0.029***	-0.026***
	(0.010)	(0.005)	(0.010)	(0.002)	(0.002)	(0.002)
Mover × Constrained	0.054**	-0.013	0.041*	-0.000	0.002	0.002
	(0.017)	(0.008)	(0.017)	(0.005)	(0.004)	(0.005)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	55,075	55,075	55,075	444,611	444,611	444,611
Adj. R^2	0.80	0.90	0.89	0.61	0.93	0.91
Panel B: Between-Occupation						
Mover	0.045**	-0.063***	-0.018	-0.010**	-0.071***	-0.081***
	(0.016)	(0.008)	(0.016)	(0.003)	(0.002)	(0.004)
Mover × Constrained	0.076***	0.002	0.078**	0.019**	0.011*	0.030***
	(0.026)	(0.012)	(0.026)	(0.007)	(0.005)	(0.008)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	52,580	52,580	52,580	427,943	427,943	427,943
Adj. R^2	0.67	0.77	0.74	0.53	0.85	0.80

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*
Note: This table presents estimates from event-study regressions specified in equation 1 considering within-occupation and between-occupation moves separately. The data used is the EEC-DADS sample between 2003 and 2023 (see Section 2.3 for details). Panel A restricts the sample to non-movers and within-occupation movers (workers who change employers while remaining in the same occupation). Panel B restricts the sample to non-movers and between-occupation movers (workers who change both employer and occupation). See Table 3 for details.

Occupations with More Hours? For constrained part-time workers, switching both firm and occupation is the main way to adjust hours. This type of mobility is associated with larger increases in hours for constrained than unconstrained workers. One potential explanation is that constrained workers move to occupations with longer hours more often than unconstrained workers do. This is hardly the case in practice: 58% of between-occupation moves by constrained workers reflect an improvement in hours based on occupational fixed effects, against 51% for unconstrained workers. The composition of employer-to-employer in terms of occupational hours thus does not primarily drive the results. Instead, the differences between constrained and unconstrained workers tend to occur for any given type of between-occupation move.

Figure A6 shows event-study estimates on hours under different specifications for both constrained and unconstrained workers. In each panel, the first two rows show estimates when I restrict the sample of between-occupation movers respectively to those moving towards occupations with more ($\uparrow h_{PCS}$) or fewer ($\downarrow h_{PCS}$) hours[18]. The estimates from both rows are similar in size, a sign that constrained workers are also able to adjust their hours when moving to occupations that are intensive in part-time work. The distinction is more relevant for full-time workers: estimates are positive and significant only for moves towards occupations with longer hours. This reflects that the ability to work overtime varies across occupations and is a binding feature of hours constraints in the full-time case. Workers who move to occupations with fewer hours ($\downarrow h_{PCS}$) likely end up in occupations where hours are concentrated at 35 hours with little overtime available.

Firms with More Hours? Then, I use a similar approach based on firms' hours policies, measured by AKM firm effects on hours[19]. I include both within-occupation and between-occupation moves and split them into two groups based on whether workers move to a firm with a higher ($\uparrow h_{AKM}$) or lower ($\downarrow h_{AKM}$) AKM firm effect than their origin firm. As with occupations, constrained and unconstrained part-time workers are distributed similarly across these two types (60% versus 54% move to higher h_{AKM} firms). Rows 3 and 4 of Figure A6 show event-study estimates for each type of firm mobility. The results are striking: for all types of workers, moving to a firm with a higher AKM effect increases hours worked, while moving to a firm with a lower ef-

[18] The variable used to represent hours at the occupation-level differs for part-time and full-time workers. As in Section 3.1, I use the share of part-time workers for part-time employees and the average number of (full-time) hours for full-time employees. Then, for part-time workers, $\uparrow h_{PCS}$ means moving to an occupation with a lower share of part-time work.

[19] See Section 3.2 for details about the estimation.

fect produces negative or no change in hours. constrained part-time workers who move to higher h_{AKM} firms see a 17% increase in hours—this fully accounts for the baseline 8.7% estimate from Table 3. These results align with the earlier findings from Section 3.2 about the importance of firm sorting in hours constraints.

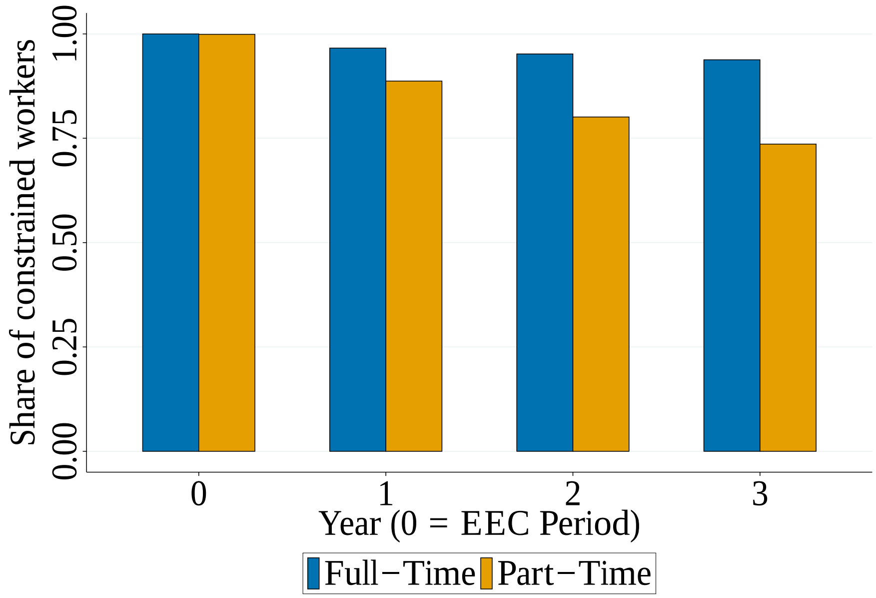
4.4 Relaxation of Hours Constraints

Section 4.2 measured how constrained workers' hours, wages, and earnings evolve differently from unconstrained workers over time. Section 4.3 explores which types of employer-to-employer mobility are associated with large variations in hours. But, ultimately, constrained workers aim to circumvent their hours constraints and find a job that better suits their hours preferences. In this section, I examine whether workers are actually able to relax their hours constraints shortly after the EEC period.

Limited Relaxation. I restrict the EEC-DADS Panel to constrained workers and use workers' self-reported ideal hours to measure the share of workers who work fewer hours than their ideal level up to 3 years after the EEC period. Figure 8 shows that most workers do not increase their hours to reach their preferred level. After three years, 26% of constrained part-time workers have closed the gap, compared to 6% of full-time workers. This difference is not driven by variation in gaps between actual and preferred hours (part-time workers in fact have larger gaps, e.g. to full-time work) Instead, it reflects differences in the ability to adjust hours, as discussed in previous sections. The proportion of workers who relax their constraints declines each year, suggesting that preferences may weaken over time or be strongest immediately after they are reported. Workers might also relax their constraints through wage increases rather than hours adjustments, since the underlying goal is likely higher earnings (see Figure B1b). However, even when I exclude workers who experience substantial wage increases (more than 10%), the proportion who relax their constraints through hours adjustments remains nearly unchanged. The figure underscores that only a limited share of constrained workers can adjust their hours to their ideal level. While previous results showed large hours adjustments for constrained workers following their EEC period, these findings reveal their concentration over few constrained workers.

Who Relaxes? Then, I examine which constrained workers are more likely to relax their constraints. For each employment status group, I regress an indicator equal to one if the individual

Figure 8: Relaxation of Hours Constraints



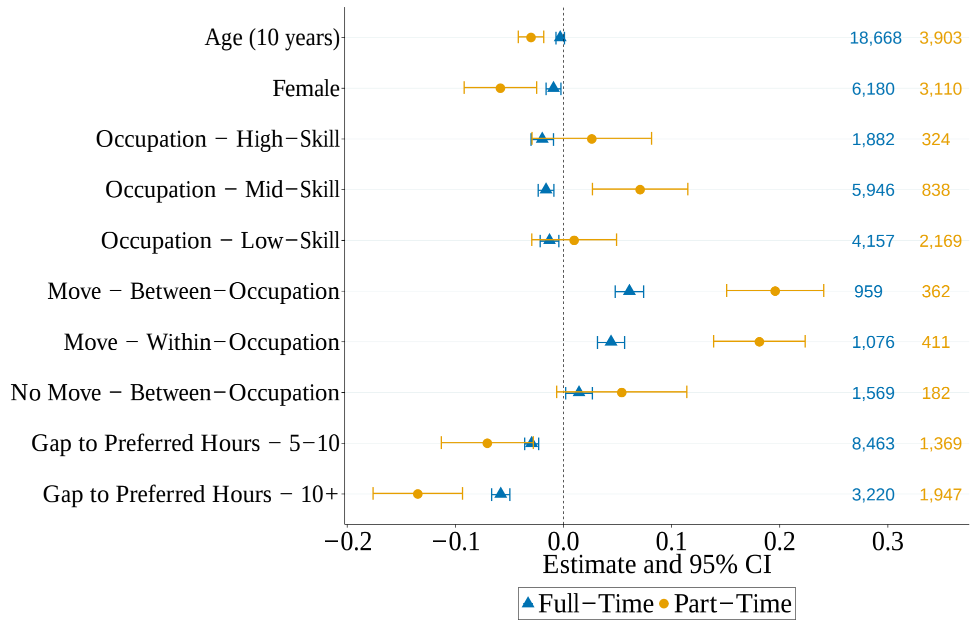
Note: The figure shows the share of constrained workers who have not reached their self-reported ideal hours level in each year following the EEC period. Ideal hours are reported during each quarter of the EEC period, and the last report is considered for this figure. The sample is restricted to constrained workers. Year 0 corresponds to the EEC period.

has reached their preferred hours level within three years after the EEC period on various covariates included jointly. Figure 9 presents the coefficient estimates alongside the number of constrained workers corresponding to each covariate value (for age, the only continuous variable, the full sample size is reported). Being older and being female both reduce the probability of relaxing constraints, particularly among part-time workers. Occupation plays a differential role across groups: among part-time workers, mid-skill workers are significantly more likely to relax their constraints compared to low-skill manual workers (the reference group), while among full-time workers, low-skill manual workers are more likely to adjust than any other group. Consistent with previous findings, employer-to-employer moves are the most effective mechanism for increasing hours to the desired level. Finally, constrained workers with smaller gaps between actual and preferred hours are, logically, more likely to relax their constraints than those facing large gaps.

4.5 Robustness Checks

This section evaluates whether three potential measurement issues affect the validity of the results. Reassuringly, the main findings remain overall robust across alternative specifications.

Figure 9: Probability to Relax Constraints



Note: This figure shows coefficient estimates from separate regressions for part-time and full-time constrained workers. The dependent variable is an indicator equal to one if the worker has reached their preferred hours level within three years after the EEC period. All covariates are included jointly. Numbers on the right indicate the sample size for each group. Reference categories for categorical variables are low-skill manual workers, workers who do not move and remain in the same occupation and gaps to preferred hours of less than 5 hours. Error bars correspond to 95% confidence intervals.

Voluntary Moves. The interpretation of job moves as reflecting revealed preferences relies on the assumption that these moves are voluntary. To test this, I re-estimate the main specification from Equation 1 using a stricter definition of mobility. A move is classified as voluntary if it originates from a permanent contract and involves less than 60 days between jobs[20]. Table A6 reveals meaningful differences from the original specification. Voluntary moves are associated with larger hour increases (5.9% for part-time and 1.5% for full-time workers) and smaller wage reductions. As a result, the combined effect on earnings becomes significantly positive for part-time workers and only slightly negative for full-time workers. For constrained part-time workers specifically, voluntary moves enable a 15% increase in hours and a 10% increase in earnings compared to those who remain with the same employer. In contrast, among full-time workers, voluntary moves produce similar effects for both constrained and unconstrained workers.

Persistent Hours Preferences. As discussed in Appendix B2, workers' hours preferences show limited persistence over time. This raises the possibility that hours constraints measured during

[20]This definition differs slightly from Babet and Chabaud (2024), as I use the starting and ending dates of employment rather than unemployment benefit receipts to determine the no-unemployment criterion.

the EEC period may not persist afterward—meaning some constrained workers may no longer wish to increase their hours in subsequent periods. To address this concern, I restrict the sample of constrained workers to those whose preferences remain identical throughout their EEC period, thereby focusing on workers with stable preferences for longer hours. Table A7 shows results broadly similar to the original specification. Estimates for unconstrained workers remain nearly unchanged as their sample is unaffected by the restriction. For constrained workers, the interaction coefficients on hours and earnings are attenuated for part-time workers but roughly doubled for full-time workers. This suggests that distinguishing between workers with stable versus unstable preferences is particularly important for understanding full-time worker behavior.

Period-Specific Estimates. To address the concern that the estimates may be driven by specific time periods, I split the sample into four subsamples, each excluding a different five-year period, and re-estimate the main results. Table A8 shows a remarkable consistency in estimates across panels for constrained workers. The primary exception is a notable decrease in the hours and earnings coefficients for part-time workers when the 2019–2023 period is excluded. This suggests that constrained part-time workers have increasingly moved toward longer hours in recent years, consistent with the view that hours constraints are an important contemporary phenomenon.

5 Willingness-To-Pay Framework

This section aims to identify workers' willingness-to-pay (WTP) to relax hours constraints building on the approach of Le Barbanchon et al. (2020).

5.1 Framework

Consider the following simple framework. A representative agent has the initial job bundle with (hourly) wage w_0 and hours h_0. Worker utility is $u(w,h) = wh - \varepsilon h^{\mu}$ from Lachowska et al. (2023), where ε captures preferences for leisure and μ measures disutility from working, with $\mu > 1$. Workers are asked (in the EEC) to report their optimal level of hours h^* at their given wage level w_0. Given this framework, the WTP can be expressed as the difference between the current wage and the wage that would provide the same utility level when working optimal hours:

$$WTP = w_0 - w\big(u(w_0, h_0), h^*\big)$$

The representative agent is observed for a number of periods after their report (as in the EEC-DADS Panel). In particular, workers can decide to move to a different job with wage-hour bundle (w_i, h_i). The method by Le Barbanchon et al. (2020) fits the parameters of the iso-utility curve by minimizing a loss function corresponding the Euclidian distance between destination job bundles (w_i, h_i) that are below the current job's iso-utility curve and their linear projection on this curve. The intuition is to draw the iso-utility curve that best rationalizes the acceptance of destination jobs in a simple job search model.

Figure 10 illustrates the strategy. Black and grey curves are two potential iso-utility curves, i.e. representing the space of wage-hour bundles that yield the same utility as the initial bundle (w_0, h_0), with different values of ε and μ. Likewise, the red curve corresponds to the level of utility derived from the optimal bundle (w_0, h^*). Green dots correspond to all destination job bundles for individuals with the initial job bundle (w_0, h_0) and optimal hours h^*. The goal of the method is to estimate ε and μ, the parameters of the utility function, in order to recover the y-axis coordinate of the blue point and compute the WTP. In this example, the black curve is the curve that satisfies the minimization problem, while the grey curve implies a higher loss function.

The optimality of the bundle (w_0, h^*), i.e. at this point the marginal utility is 0, allows to write ε with respect to μ, thus to reduce the optimization problem to one parameter.

$$\left.\frac{\partial u}{\partial h}\right|_{w=w_0, h=h^*} = 0 \Leftrightarrow w_0 - \mu\varepsilon {h^*}^{\mu-1} = 0 \Leftrightarrow \varepsilon = \frac{w_0}{\mu {h^*}^{\mu-1}}$$

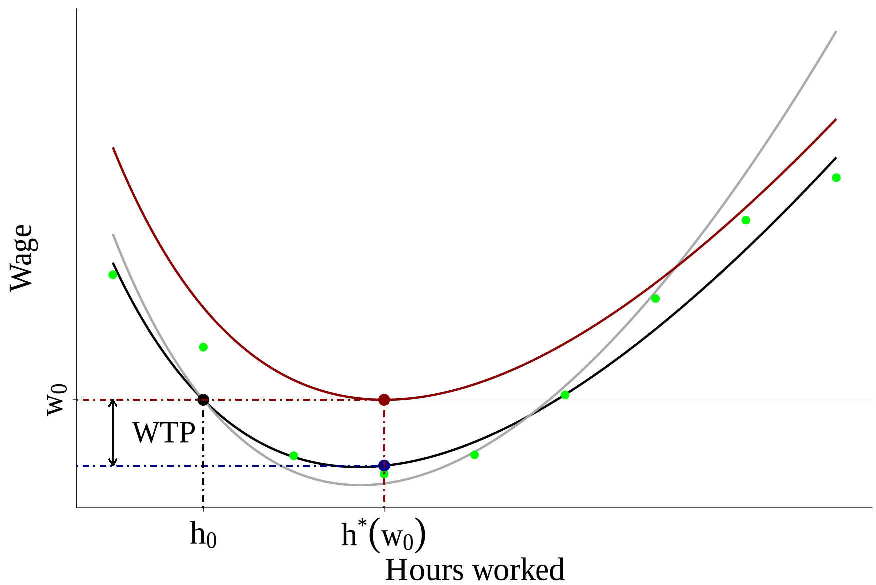
The optimization problem then becomes almost identical to Le Barbanchon et al. (2020)'s estimation of the slope parameter. Denote $\mathcal{B}_\mu$ the set of destination job bundles below the current job's iso-utility curve ($\mathcal{B}_\mu = \{i \mid u(w_i, h_i) < u(w_0, h_0)\}$). The target estimator of the parameter can then be written as:

$$\hat{\mu} = \text{argmin}_\mu \sum_{i \in \mathcal{B}_\mu} d_{\mu, w_0, h_0} (w_i, h_i)^2$$

5.2 Estimation

This section describes the implementation of the strategy. I restrict the EEC-DADS panel to constrained workers who switch firms between 1 and 3 years after the EEC period, yielding a sample of 13,292 workers. I group workers by triplet (w_0, h_0, h^*), where w_0 is rounded to the

Figure 10: Willingness-To-Pay Framework

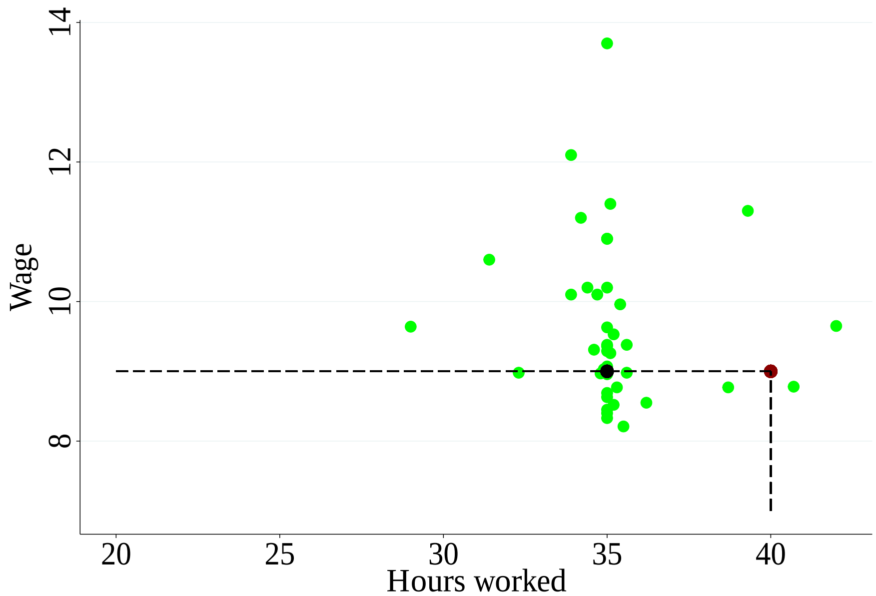


Note: The figure illustrates the framework for estimating willingness-to-pay (WTP) to relax hours constraints. The initial job bundle (w_0, h_0) and the worker's optimal hours h^* are shown. Black and grey curves represent potential iso-utility curves through (w_0, h_0) with different parameter values in the utility function $u(w, h) = wh - \varepsilon h^\mu$. The red curve shows the iso-utility curve through the optimal bundle (w_0, h^*). Green dots represent observed destination job bundles (w_i, h_i). The estimation method identifies utility parameters by minimizing the Euclidean distance between destination bundles below the iso-utility curve and their projections onto it. The black curve best fits the observed transitions. WTP is the vertical distance between the blue point at h^* and w_0, representing the wage reduction a worker would accept to work optimal hours while maintaining utility.

nearest decimal and h_0 is rounded to the nearest digit, and remove all triplets with less than 10 workers. For each conserved triplet, the set of destination bundles contains at least 10 bundles to estimate the parameter μ. However, one potential threat is that all bundles would be very similar which would make the estimation invalid. Figure 11 shows the set of destination bundles for the triplet $(9, 35, 40)$. Reassuringly, I observe some variation in hours and wages on both sides of the initial job bundle, i.e. either driven by higher wages or longer hours.

I solve the optimization problem by using a grid search approach. For each candidate μ, I then examine all destination job bundles (w_i, h_i). I first check whether each bundle lies below the corresponding initial job's iso-utility curve by comparing $u(w_i, h_i)$ to $u(w_0, h_0)$. For bundles that fall below this curve, I compute their Euclidean distance to the curve by finding their closest point on the curve. This closest point (h_i^p, w_i^p) is found by solving for the point on the iso-utility curve where the derivative of the squared distance with respect to hours equals zero. The squared distance is then $(h_i^p - h_i)^2 + (w_i^p - w_i)^2$.

Figure 11: Example of the Set of Destination Bundles



Note: The figure provides an example of a set of destination bundles for workers with $w_0 = 9$, $h_0 = 35$ and $h^* = 40$. The initial job bundle (w_0, h_0) and the worker's optimal hours h^* are shown respectively in black and red. Green dots represent observed destination job bundles (w_i, h_i).

The loss function for each candidate μ is the sum of squared distances across all destination bundles that lie below the initial iso-utility curve. The estimated parameter $\hat{\mu}$ is the value that minimizes this total loss. Once $\hat{\mu}$ is identified, I recover $\hat{\varepsilon}$ from the optimality condition and use these parameters to recover for each worker the WTP as the vertical distance between this curve and w_0 at hours h^*.

The estimation yields $\hat{\mu} = 3.12$, which results in an average willingness-to-pay of 1.6% for workers to reach their preferred number of hours. This estimate is of small magnitude compared to Lachowska et al. (2023). It is explained by the strong reliance on full-time workers, the most current type, in the estimation process who do not experience large changes in hours nor wages through their mobility, as shown in Section 4. Next steps on this project should try to refine the estimation procedure in order to provide estimates for most constrained workers.

6 Conclusion

This paper builds on a unique data linkage to produce an innovative empirical study on hours constraints in France. By combining self-reported hour preferences from the Labor Force Survey with administrative employer-employee records, I provide evidence that hours constraints play a significant role in labor market dynamics. The analysis underscores how occupational and firm sorting shape these constraints and delivers the first evidence on workers' ability to adjust their hours over time. Preliminary estimates of workers' willingness to pay to reach their preferred schedules point to non-negligible welfare costs associated with such constraints.

More broadly, this study introduces a comprehensive empirical framework for analyzing constraints in the labor market. By focusing on working time, it sheds light on the importance of non-wage job characteristics in shaping labor outcomes. The findings carry key implications for policymakers, as hours constraints are widespread in the workforce, and researchers, as working hours are central to the economic structure. In a context of evolving work, my research calls for rethinking work organization and employer-employee relations, particularly from the perspective of labor demand.

References

Abowd, J. M. and Card, D. (1987). Intertemporal Labor Supply and Long-term Employment Contracts. *American Economic Review*, 77(1):50–68.

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High Wage Workers and High Wage Firms. *Econometrica*, 67(2):251–333.

Altonji, J. G. and Paxson, C. H. (1986). Job Characteristics and Hours of Work. *NBER Working Papers*, (1895).

Asai, K. (2024). Gender Differences in the Effects of Reducing Working Hours. *Unpublished Manuscript*.

Babet, D. and Chabaud, M. (2024). Follow the Money ? Workers' Mobility, Wages and Amenities. *Insee Working Papers*, (19).

Beckmannschagen, M. and Schröder, C. (2022). Earnings Inequality and Working Hours Mismatch. *Labour Economics*, 76.

Bell, D. N. F. and Blanchflower, D. G. (2021). Underemployment in the United States and Europe. *ILR Review*, 74(1):56–94.

Bick, A., Blandin, A., and Rogerson, R. (2022). Hours and Wages. *Quarterly Journal of Economics*, 137(3):1901–62.

Bick, A., Fuchs-Schündeln, N., and Lagakos, D. (2018). How Do Hours Worked Vary with Income? Cross-Country Evidence and Implications. *American Economic Review*, 108(1):170–199.

Bloemen, H. G. (2008). Job Search, Hours Restrictions, and Desired Hours of Work. *Journal of Labor Economics*, 26(1):137–179.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting Event-Study Designs: Robust and Efficient Estimation. *The Review of Economic Studies*, 91(6):3253–3285.

Breda, T., Pecheu, V., and Roux, B. (2025). When Workers Don't Know Their Contract: Evidence from French Working Time Regulations. *Unpublished manuscript*.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-Differences with Multiple Time Periods. *Journal of Econometrics*, 225(2):200–230.

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics*, 128(3):967–1015.

Chetty, R., Friedman, J. N., Olsen, T., and Pistaferri, L. (2011). Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records. *Quarterly Journal of Economics*, 126(2):749–804.

Costa, D. L. (2000). The Wage and the Length of the Work Day: From the 1890s to 1991. *Journal of Labor Economics*, 18(1):156–181.

Dickens, W. and Lundberg, S. J. (1993). Hours Restrictions and Labor Supply. *International Economic Review*, 34:169–192.

Dube, A., Naidu, S., and Reich, A. D. (2022). Power and Dignity in the Low-Wage Labor Market: Theory and Evidence from Wal-Mart Workers. Working Paper 30441, National Bureau of Economic Research.

Frazis, H. and Stewart, J. (2010). Why Do BLS Hours Series Tell Different Stories About Trends in Hours Worked? In *Labor in the New Economy*, NBER Chapters, pages 343–372. National Bureau of Economic Research, Inc.

Gaini, M. and Vicard, A. (2012). Les Salariés Qui Souhaitent Travailler Davantage y Parviennent-Ils? Technical report, Insee France Portrait Social.

Godechot, O., Palladino, M. G., and Babet, D. (2023). In the Land of AKM: Explaining the Dynamics of Wage Inequality in France. *SciencesPo Working papers*.

Hwang, H., Mortensen, D., and Reed, W. (1998). Hedonic Wages and Labor Market Search. *Journal of Labor Economics*, 16(4):815–47.

Jarosch, G., Pilossoph, L., and Swaminathan, A. (2025). Should Friday be the New Saturday? Hours Worked and Hours Wanted. NBER Working Papers 33577, National Bureau of Economic Research, Inc.

Kahn, S. and Lang, K. (1991). The Effect of Hours Constraints on Labor Supply Estimates. *Review of Economics and Statistics*, pages 605–611.

Kahn, S. and Lang, K. (2001). Hours Constraints: Theory, Evidence, and Policy Implications. In Wong, G. and Picot, G., editors, *Working Time in Comparative Perspective: Patterns, Trends, and the*

Policy Implications of Earnings Inequality and Unemployment, Volume I, chapter 8, pages 261–287. Upjohn Institute Press.

Labanca, C. and Pozzoli, D. (2022). Constraints on Hours within the Firm. *Journal of Labor Economics*, 40(2).

Labanca, C. and Pozzoli, D. (2023). Hours Constraints and Wage Differentials across Firms. *Journal of Human Resources*.

Lachowska, M., Mas, A., Saggio, R., and Woodbury, S. (2023). Work Hours Mismatch. *NBER Working Paper No. w31205*, pages 317–346.

Lachowska, M., Mas, A., and Woodbury, S. A. (2022). How Reliable are Administrative Reports of Paid work Hours? *Labour Economics*, 75:102–131.

Lamadon, T., Mogstad, M., and Setzler, B. (2022). Imperfect Competition, Compensating Differentials, and Rent Sharing in the U.S Labor Market. *American Economic Review*, 112(1):169–212.

Lang, K. and Majumdar, S. (2004). The Pricing of Job Characteristics When Markets Do Not Clear: Theory and Policy Implications. *International Economic Review*, 45(4):1111–1128.

Lavetti, K. and Schmutte, I. M. (2016). Estimating Compensating Wage Differentials with Endogenous Job Mobility. *Unpublished manuscript*.

Le Barbanchon, T., Rathelot, R., and Roulet, A. (2020). Gender Differences in Job Search: Trading off Commute against Wage. *The Quarterly Journal of Economics*, 136(1):381–426.

Lewis, H. G. (1967). Employer Interests in Employee Hours of Work. *Unpublished manuscript*.

Lewis, H. G. (1969). Interes del Empleador en las Horas de Trabajo del Empleado. *Cuadernos de Economia*, 6(18):38–54.

Pencavel, J. (2015). Whose Preferences Are Revealed in Hours of Work? *IZA Discussion Papers*, (9182).

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82(1):34–55.

Rosen, S. (1986). Chapter 12: The Theory of Equalizing Differences. In *Handbook of Labor Economics*, volume 1, pages 641–692. Elsevier.

Sorkin, I. (2018). Ranking Firms Using Revealed Preference. *Quarterly Journal of Economics*, 133(3):1331–1393.

Stantcheva, S. (2023). How to Run Surveys: A Guide to Creating Your Own Identifying Variation and Revealing the Invisible. *Annual Review of Economics*, 15(1):205–234.

Appendix A Additional Figures and Tables

Table A1: EEC and Matched EEC-DADS Samples, 2003-2023

		EEC Sample	EEC Sample (with *SIRET*)	EEC-DADS Sample	EEC-DADS Panel
Number of observations		3,201,635	2,619,074	1,695,359	9,734,018
Number of workers		791,701	654,632	435,472 (67%)	399,553 (61%)
Number of firms		262,823	262,823	196,484	612,603
Full-Time (%)		81.0	82.7	82.8	82.8
Female (%)		50.4	49.3	48.4	49.4
Age	15-24	8.3	8.1	8.5	13.4
	25-34	20.6	20.8	21.3	24.6
	35-44	26.0	26.3	26.9	25.1
	45-54	28.3	28.4	27.9	24.1
	55+	16.7	16.3	15.5	12.8
Occupation (%)	High-Skill	17.4	18.1	17.3	17.4
	Mid-Skill	26.4	27.5	27.3	26.4
	Low-Skill Non-Manual	32.2	30.2	28.8	30.4
	Low-Skill Manual	24.0	25.0	26.6	25.7
Firm Size (%)	< 10	59.1	57.6	58.2	58.7
	10-49	15.4	16.0	16.6	17.3
	50-499	17.3	18.1	18.2	17.5
	> 500	8.2	8.3	7.0	6.5
Usual Hours Worked (%)	< 25	10.4	9.0	8.6	11.8
	25-34	10.0	9.9	9.7	10.0
	35-39	52.5	55.1	55.9	53.0
	40-49	19.5	18.9	18.9	18.0
	≥ 50	7.6	7.1	7.0	7.2
Share of constrained from above - Full-time (%)		16.3	16.9	19.0	19.5
Share of constrained from above - Part-time (%)		34.7	33.8	26.0	23.8
Share of involuntary part-time workers (%)		24.2	24.3	19.0	17.1
Share of constrained from below (%)		2.4	2.5	2.5	2.5

Note: This table compares the two newly built EEC-DADS and EEC-DADS Panel samples with the original EEC sample. The EEC sample (with *SIRET*) corresponds to the EEC sample after removing observations where the establishment's ID is missing. Shares of constrained and involuntary part-time workers are computed in proportion of the corresponding working time status considering the workers' last quarter of observation.

Table A2: Summary Statistics of Constrained Workers in EEC-DADS and EEC

	Involuntary Part-Time		**Full-Time**	
Variable	EEC	EEC-DADS	EEC	EEC-DADS
Age	37.1	38.1	37.8	37.5
Female (%)	73.8	71.8	61.5	58.6
Occupation - High-Skill (%)	4.0	4.6	10.8	9.9
Occupation - Mid-Skill (%)	16.4	12.7	27.8	22.1
Occupation - Low-Skill Non-Manual (%)	58.3	60.0	27.4	31.1
Occupation - Low-Skill Manual (%)	21.4	22.7	33.9	36.9
Born Abroad (%)	13.8	12.7	10.8	10.5
Public Sector (%)	23.7	19.6	17.6	13.0
Permanent Contract, *CDI* (%)	58.4	71.7	83.3	83.2
Usual Hours Worked	23.3	26.4	37.3	35.6

Note: This table presents summary statistics of constrained workers in the EEC and EEC-DADS samples. ”Female” shows the proportion of females. Occupation categories correspond to the 1st-digit in the PCS classification, respectively 3, 4, 5 and 6. ”Born Abroad” indicates the proportion of individuals born outside of France. ”Public Sector” shows the proportion of workers in the public sector. ”Permanent Contract, CDI” represents the share of workers with a permanent contract (*contrat à durée indéterminée*).

Table A3: Summary Statistics by Group of Workers’ Preferences

Variable	**Constrained from above**	**Constrained from below**	**Unconstrained**
Age	38.6	43.9	42.8
Female (%)	48.7	61.2	49.1
Occupation - High-Skill (%)	8.9	31.4	20.2
Occupation - Mid-Skill (%)	24.9	32.1	28.2
Occupation - Low-Skill Non-Manual (%)	37.1	24.6	28.8
Occupation - Low-Skill Manual (%)	29.2	11.9	22.7
Born Abroad (%)	11.9	8.2	10.3
Public Sector (%)	20.1	24.1	23.7
Permanent Contract, *CDI* (%)	80.9	94.9	91.8
Share of Part-Time (%)	28.0	11.2	14.5
Usual Hours Worked (Full-Time)	37.2	40.9	39.0

Note: This table presents summary statistics by group of preferences on working hours. Groups are considered based on their answers to the following questions in the surveys: *”do you ideally want to work* [more/less] *hours in your job with a corresponding income variation?”*. ”Constrained from above” workers report that they ideally want to work more hours ; ”Constrained from below” workers report that they ideally want to work less hours ; ”Unconstrained” workers answer no to both questions. ”Age” represents mean age in years. ”Female” shows the proportion of females. Occupation categories correspond to the 1st-digit in the PCS classification, respectively 3, 4, 5 and 6. ”Born Abroad” indicates the proportion of individuals born outside of France. ”Public Sector” shows the proportion of workers in the public sector. ”Permanent Contract, CDI” represents the share of workers with a permanent contract (*contrat à durée indéterminée*). The final row reports average hours worked of workers with full-time contracts.

Table A4: Gap in Hours Between Constrained and Unconstrained Workers

Dependent Variables:	*Log Hours*									
	Paid Hours Worked (DADS)					Usual Hours Worked (EEC)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constrained	-0.029***	-0.032***	-0.022***	-0.010***	-0.003***	-0.053***	-0.059***	-0.048***	-0.037***	-0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls and Fixed-effects										
Year	X	X	X	X	X	X	X	X	X	X
Demographics		X	X	X	X		X	X	X	X
Occupation			X	X	X			X	X	X
Workplace				X	X				X	X
Part-/Full-Time					X					X
Baseline	32.2	32.2	32.2	32.2	32.2	35.8	35.8	35.8	35.8	35.8
Observations	222,152	222,152	222,152	222,152	222,152	222,152	222,152	222,152	222,152	222,152
Adj. R^2	0.00	0.06	0.12	0.49	0.65	0.01	0.08	0.17	0.52	0.61

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*
Note: This table presents OLS estimates of the difference in hours worked between workers labeled as constrained (from above) and unconstrained. The data used is the EEC-DADS sample between 2003-2023 (see Section 2.3 for more details) and consists of 222,152 workers after the sample has been restricted to workplaces with at least one constrained and one unconstrained worker. The dependent variable is log paid hours worked from the DADS in columns 1-5 and log usual hours worked from the EEC in columns 6-10. Demographics include age, gender, and county of residence. Occupations correspond to the 3-digit level in the PCS classification (110 levels). Occupations with more than 20% of forfait jours workers in the EEC between 2013 and 2023 are excluded from the sample. Standard errors are heteroskedasticity-robust and reported in parentheses.

Table A5: Within-Firm Determinants of Hours Constraints - Falsification Test

Dependent Variable:	Age					Female	Experience	Foreigner	Distance
	15-24	25-34	35-44	45-54	55+				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Full-Time (EEC-DADS)	0.009	0.048**	0.039*	-0.040*	-0.056***	-0.083***	0.041	0.002	0.963
	(0.010)	(0.018)	(0.005)	(0.019)	(0.019)	(0.014)	(0.018)	(0.012)	(2.210)
Observations	40,425	40,425	40,425	40,425	40,425	40,425	40,425	40,425	40,425
Triplets	1,244	1,244	1,244	1,244	1,244	1,244	1,244	1,244	1,244
Adj. R^2	0.17	0.15	0.07	0.11	0.12	0.38	0.49	0.33	0.47
Controls and Fixed Effects									
Year × Workplace × Occupation	X	X	X	X	X	X	X	X	X
Age (Polynomial)						X	X	X	X
Female	X	X	X	X	X		X	X	X
Experience	X	X	X	X	X	X		X	X
Foreigner	X	X	X	X	X	X	X		X
Distance	X	X	X	X	X	X	X	X	

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*
Note: This table presents a falsification test to the approach undertaken in Section 3.3. The sample includes all triplets (year × workplace × occupation) with at least one involuntary part-time worker. Each column reports results from a separate OLS regression where the coefficient indicates the difference in the specified characteristic between full-time workers from and from the DADS. See Table 1 for more details about each variable. Standard errors are clustered at the year × workplace × occupation level and reported in parentheses.

Table A6: Event-Study Effects on Hours, Wages and Earnings - Voluntary Moves

Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Mover	0.059***	-0.023**	0.037***	0.015***	-0.023***	-0.008**
	(0.012)	(0.007)	(0.012)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.094***	-0.030*	0.064**	0.005	-0.003	0.001
	(0.026)	(0.013)	(0.025)	(0.006)	(0.004)	(0.006)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline	25.4	13.8	18,341	34.6	16.5	29,595
Observations	57,439	57,439	57,439	466,261	466,261	466,261
Adj. R^2	0.80	0.90	0.89	0.61	0.93	0.91

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents estimates from event-study regressions specified in equation 1 using the alternative definition of employer-to-employer moves similar to Babet and Chabaud (2024). The data used is the EEC-DADS sample between 2003 and 2023 (see Section 2.3 for details). The sample is restricted to moves from a permanent contract with an unemployment period of less than 60 days between jobs. See Table 3 for details.

Table A7: Event-Study Effects on Hours, Wages and Earnings - Stable Constrained Workers

Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours (1)	Wages (2)	Earnings (3)	Hours (4)	Wages (5)	Earnings (6)
Mover	0.024**	-0.040***	-0.016	-0.002	-0.046***	-0.048***
	(0.009)	(0.004)	(0.009)	(0.002)	(0.001)	(0.002)
Mover × Constrained	0.043**	-0.005	0.039*	0.016***	0.005	0.021***
	(0.017)	(0.008)	(0.025)	(0.005)	(0.004)	(0.005)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Baseline	25.4	13.9	18,438	34.6	16.6	29,782
Observations	56,125	56,125	56,125	455,484	455,484	455,484
Adj. R^2	0.78	0.89	0.88	0.60	0.93	0.90

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

Note: This table presents estimates from event-study regressions specified in equation 1 using an alternative definition of constrained workers with stable preferences over their EEC period. The data used is the EEC-DADS sample between 2003 and 2023 (see Section 2.3 for details). The sample is restricted to moves from a permanent contract with an unemployment period of less than 60 days between jobs. See Table 3 for details.

Table A8: Event-Study Effects on Hours, Wages and Earnings - Specific Periods

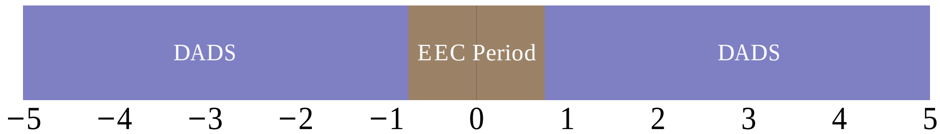
Group (EEC Period):	**Part-Time**			**Full-Time**		
Dependent Variable (in logs):	Hours	Wages	Earnings	Hours	Wages	Earnings
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 2009-2023						
Mover	0.025**	-0.039***	-0.014	-0.001	-0.046***	-0.047***
	(0.009)	(0.004)	(0.009)	(0.002)	(0.001)	(0.002)
Mover × Constrained	0.065***	-0.008	0.057***	0.007	0.004	0.011*
	(0.015)	(0.007)	(0.015)	(0.004)	(0.003)	(0.005)
Panel B: 2003-2008, 2014-2023						
Mover	0.035***	-0.046***	-0.011	0.003	-0.048***	-0.045***
	(0.010)	(0.005)	(0.010)	(0.002)	(0.002)	(0.002)
Mover × Constrained	0.056**	-0.002	0.054**	0.003	0.003	0.006
	(0.017)	(0.008)	(0.017)	(0.005)	(0.004)	(0.005)
Panel C: 2003-2013, 2019-2023						
Mover	0.040***	-0.045***	-0.005	0.003	-0.048***	-0.045***
	(0.012)	(0.006)	(0.012)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.064**	-0.002	0.062**	0.009	0.003	0.012*
	(0.021)	(0.008)	(0.020)	(0.006)	(0.004)	(0.006)
Panel D: 2003-2018						
Mover	0.002	-0.030***	-0.028*	-0.015***	-0.041***	-0.056***
	(0.012)	(0.006)	(0.012)	(0.002)	(0.002)	(0.003)
Mover × Constrained	0.066**	-0.020*	0.046*	0.011	0.005	0.016**
	(0.021)	(0.009)	(0.021)	(0.006)	(0.004)	(0.006)
Fixed effects						
Worker FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Observations - Part-Time: A = 59,102 ; B = 46,769; C = 37,665; D = 37,706.
Observations - Full-Time: A = 469,357 ; B = 356,885 ; C = 310,121; D = 313,447.

*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05.*

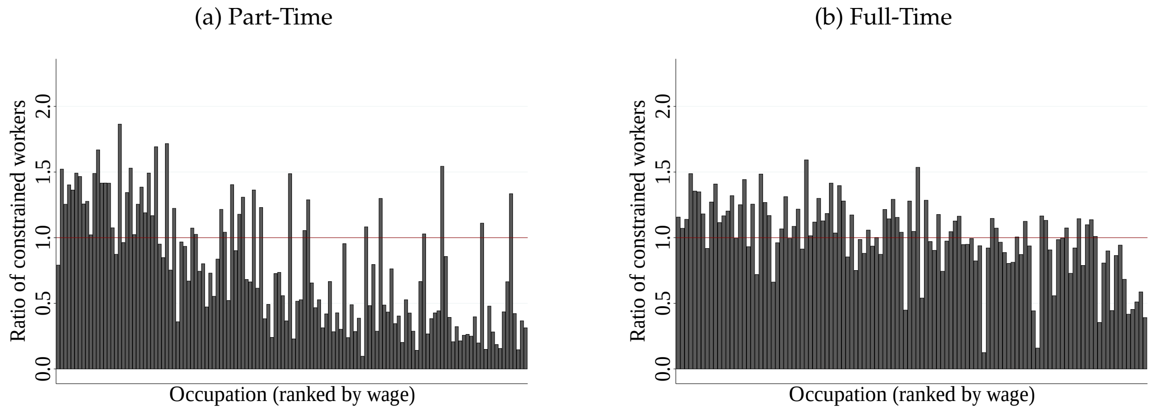
Note: This table presents estimates from event-study regressions specified in equation 1 using using four subsamples, each excluding a different five-year period. The data used is the EEC-DADS sample between 2003 and 2023 (see Section 2.3 for details). See Table 3 for details.

Figure A1: EEC-DADS Panel Data



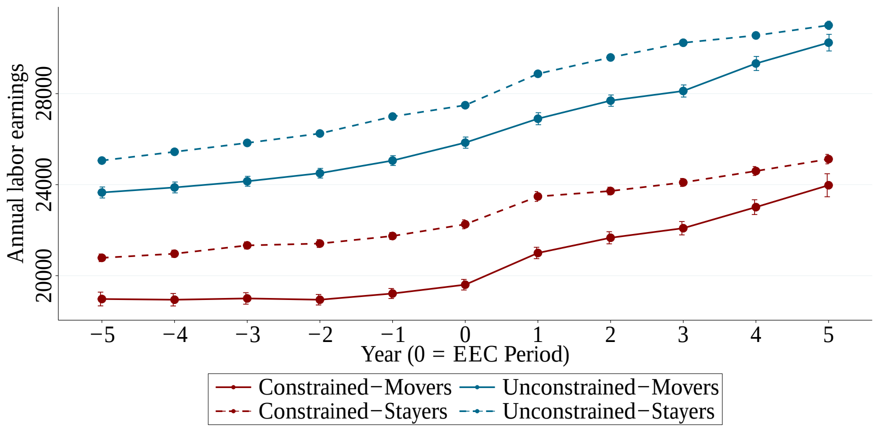
Note: This figure illustrates the structure of the newly built EEC-DADS panel data. This dataset is constructed based on the EEC-DADS dataset and the DADS panel from Godechot et al. (2023). It combines for each individual EEC-based information over 6 quarters of observation (the EEC period) and DADS-based information over the period of appearance in the panel. See Section 2.3 for more details.

Figure A2: Representativity of Constrained Workers by Occupation



Note: The figures show the ratio of the distribution of constrained (from above) workers to the overall distribution of workers across occupations by working time status. Data is based on Labor Force Surveys pooled between 2003 and 2023. Each bar corresponds to an occupation (ranked by wage) at the 3-digit level in the PCS classification (110 levels). Occupations with less than 10 workers are removed from the sample. The y-axis indicates the proportion of the population constrained from above that works in a given occupation divided by the proportion of the total population that works in this occupation. An individual is constrained from above if he or she answers yes to the question: *"do you ideally want to work more hours in your job with a corresponding income variation?"* in the Labor Force Survey.

Figure A3: Evolution of Earnings in the EEC-DADS Panel

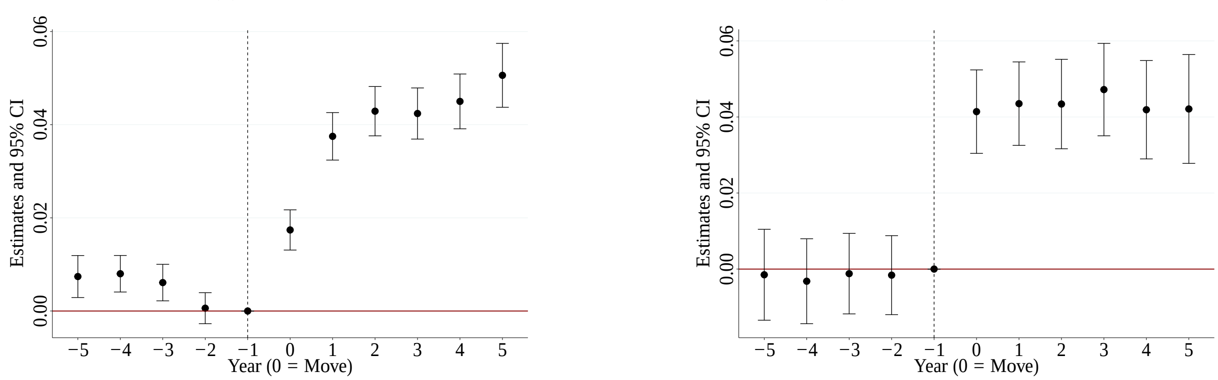


Note: This figure represents the evolution of earnings across employer-to-employer transitions for different worker groups. The x-axis shows years relative to the EEC period, while the y-axis displays average annual earnings. The data used is the EEC-DADS sample (see Section 2.3 for details). Four distinct groups are tracked: constrained-movers (solid red line), unconstrained-movers (solid blue line), constrained-stayers (dashed red line), and unconstrained-stayers (dashed blue line). Workers are classified as constrained or unconstrained based on their reported hour preferences, and as movers or stayers based on whether they switch employers during years 1 to 3 after the observation period. Error bars correspond to 95% heteroskedasticity-robust confidence intervals.

Figure A4: Event-Study of Employer-to-Employer Moves on Hours Worked

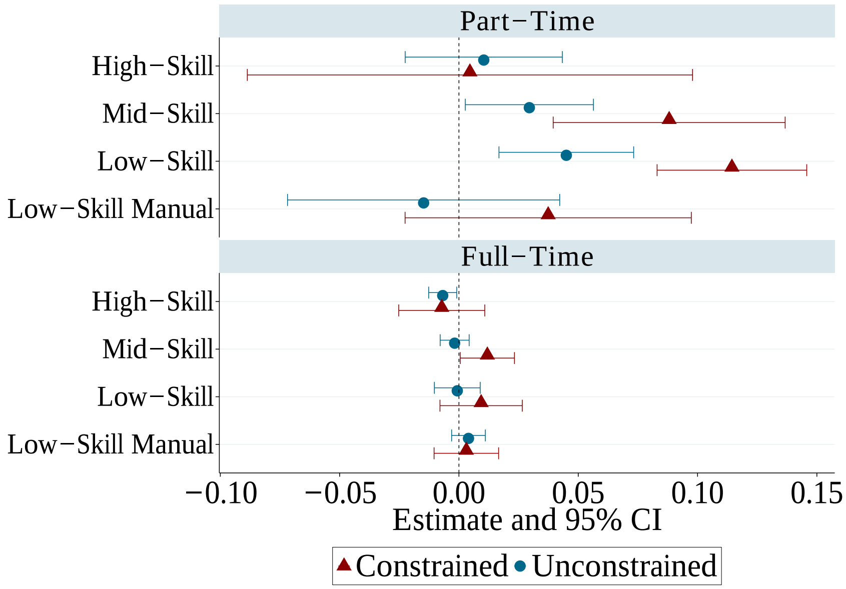
(a) Mover

(b) Mover × Constrained



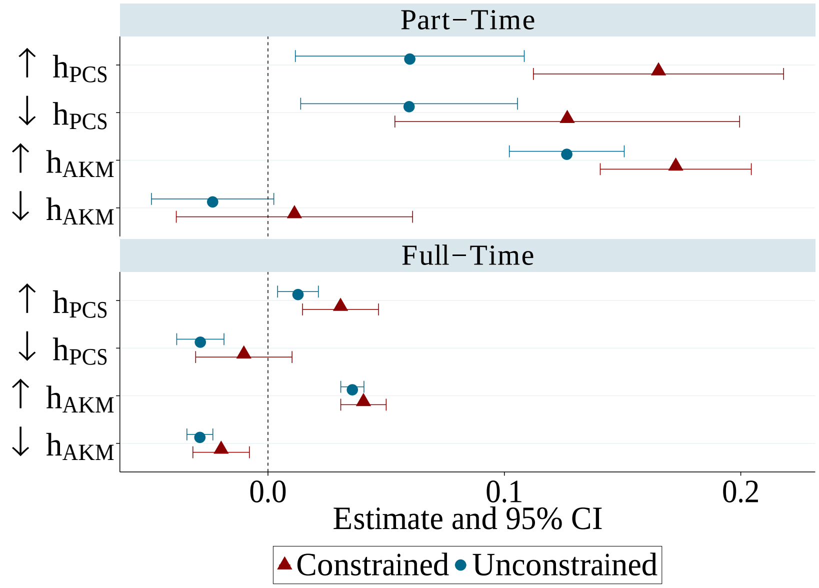
Note: Panel (a) shows event-study coefficients for the effect of employer-to-employer moves on weekly hours worked, following Callaway and Sant'Anna (2021), using never-treated individuals (non-movers) as control group. Panel (b) displays the interaction coefficients testing for differential move effects between constrained and unconstrained workers. Year 0 corresponds to the year of the employer-to-employer move. Point estimates are shown with 95% confidence intervals. Standard errors are clustered at the individual level.

Figure A5: Event-Study Effects by Type of Workers



Note: This figure shows event-study estimates on hours worked for constrained (red triangles) and unconstrained (blue circles) workers by type of worker. The specification differs from Equation 1 (and Table 3) as the interaction term is excluded and separate regressions are run for constrained and unconstrained workers to estimate β_1. See Table 3 for details about the variable used for mobility. The sample is split by workers' broad occupation during the EEC period. Occupations respectively correspond to the 1st-digit 3, 4, 5 and 6 in the PCS classification.

Figure A6: Event-Study Effects by Type of Mobility



Note: This figure shows event-study estimates on hours worked for constrained (red triangles) and unconstrained (blue circles) workers by type of mobility. The specification differs from Equation 1 (and Table 3) as the interaction term is excluded and separate regressions are run for constrained and unconstrained workers to estimate β_1. See Table 3 for details about the variable used for mobility. The sample of movers is alternatively restricted to specific types of mobility. The first two rows show estimates for between-occupation movers split by whether they move to an occupation with more ($\uparrow h_{PCS}$) or fewer ($\downarrow h_{PCS}$) hours than their origin occupation. The last two rows show estimates for all movers (both within-occupation and between-occupation) split by whether they move to a firm with a higher ($\uparrow h_{AKM}$) or lower ($\uparrow h_{AKM}$) AKM firm effect on hours than their origin firm. The estimation of AKM firm effects is detailed in Section 3.2. Non-movers serve as the comparison group for all estimates. Error bars correspond to 95% heteroskedasticity-robust confidence intervals.

Appendix B Measurement Issues and Data Linkage

B.1 Survey Measurement of Hours Constraints

This section provides additional background validation checks to the Labor Force Survey variables used to measure hours constraints. The paper relies on a certain interpretation of workers' answers to the corresponding questions. I argue that positive answers to the STPLC question reveal a concrete and thoughtful preference for working additional hours.

Methods to Increase Hours. Workers who report constraints from above and are available to work more hours are asked in a follow-up question (CSTPLC) about their preferred method to increase their hours with a list of possible items. 75% of these workers wish to work longer in their current job, while only 5% would rather take an additional job, 6% would opt to change jobs entirely, and 14% would do so by any means. The fact that a large majority of workers consider increasing their hours in their current working context supports the interpretation of the measure as embedded in real life context. Workers who are constrained from above thus do not appear to answer the question from a utopian perspective.

Motivations. Additional information from the EEC allows to evaluate the consistency of workers' reports with their motivations. Figure B1a shows the answers to the question *"What is the main reason you work part-time?"* (RAISTP), asked to part-time workers. Almost every involuntary part-time worker, who represent 75% of constrained (from above) part-time workers, reports being primarily limited by the absence of full-time jobs. On the other hand, part-time workers who do not wish to work longer hours typically cite personal factors like family reasons or free time as their main motivation for part-time work. The gap in that dimension between both types of workers is consistent with the measurement of constraints. Surprisingly, a non-negligible share of unconstrained workers, 20%, also report the unavailability of full-time contracts as their motivation for part-time work. This suggests a possible underestimation of the share of involuntary part-time workers. I adopt a similar approach with a question regarding motivations for another job (CREACCP). Focusing on the period between 2013 and 2023 (because of a break in series in 2013), I analyze answers to the question *"Why do you want another job?"* asked to workers who report that they want another job (either in replacement or in addition to the current one), with multiple possible answers in a list of items. Figure B1b shows that reports of a higher ideal number of hours are associated with prospects of increased earnings and hours. Beyond the consistency of both variables, this illustrates that the desire to work long hours is likely strongly motivated by the perspective of higher earnings. Positive answers to the STPLC question thus convey ambition for a higher income at the cost of additional hours. This interpretation makes the measurement of hours constraints through the STPLC question coherent with traditional labor supply models and sets the stage for a welfare analysis of hours constraints.

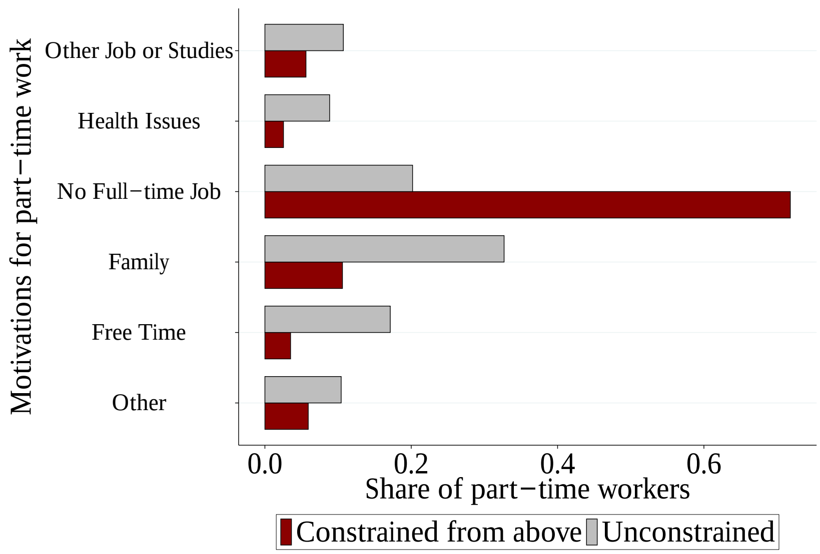
Persistence of Hours Preferences. An important question lies in understanding the stability of hours preferences over time. Individuals surveyed in the EEC are asked to report their preferences during 6 consecutive quarters at most which allows me to measure the persistence of STPLC over this period. I find that 63% of individuals who report constraints from above during their last interrogation, a definition that I use throughout Section 4, also report the same type of constraints in their first interrogation. This proportion marginally increases to 70% when only considering part-time workers but remains quite low. Additional checks suggest that the instability of preferences is not driven by changes in the employment context (employer, occupation, contract, hours worked) of the individual. This aspect of the variable is a potential threat to the results in Sections 4 and 5 which extrapolate preferences on hours over the years following the EEC period. To address this issue, I provide a robustness check in Section 4.5 where I change my definition of constrained individuals to workers who report constraints both at their first and last interrogation in the EEC period. XXX

Worker Mobility. Figure B2 also exploits the quarterly longitudinal structure of the EEC to examine the connection between reported preferences for hours and employer-to-employer mobility. Workers who report an ideal number of hours superior to their current one on their first interrogation switch employers significantly more than both unconstrained workers and workers who would ideally reduce their hours[21]. Half of individuals who move report being unconstrained in their last interrogation. This finding suggests that positive answers to the STPLC question are associated with workplace disutility, hence with mobility towards alternative employers. As a result, it reinforces the interpretation of questions regarding ideal working hours as indicative of hours constraints faced by workers.

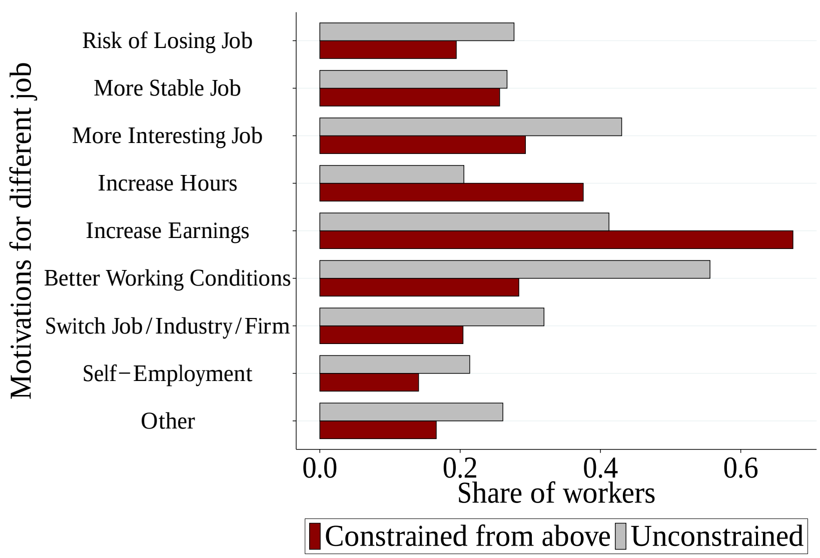
[21] The result is robust to the introduction of controls on age, gender and occupation.

Figure B1: Motivations of Constrained and Unconstrained Workers

(a) Motivations for Part-Time Work

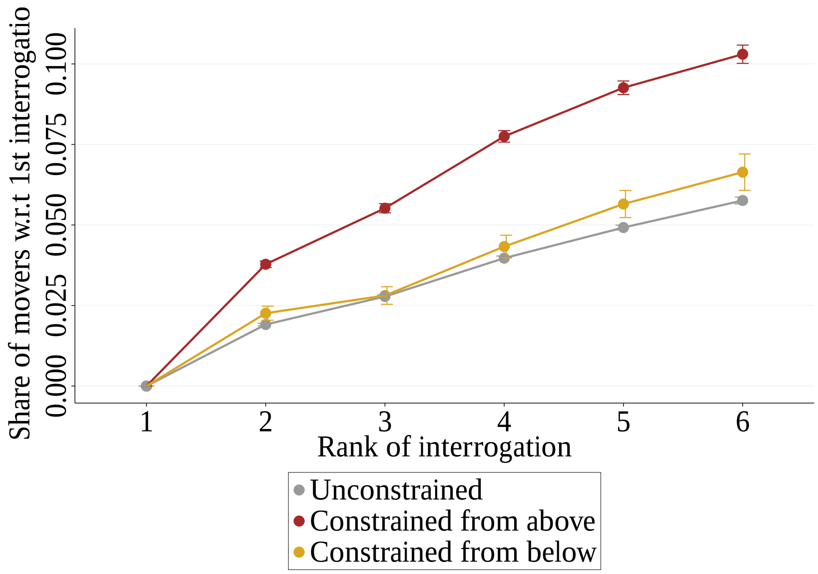


(b) Motivations for Different Job



Note: These figures represent the motivations of workers to work as part-time or to look for a different job based on their constraint status in the labor market. Workers are classified as *constrained from above* or *unconstrained* based on their answer to the STPLC question in the Labor Force Survey. See 2.1 for more details.
(a) The figure reports answers to the question *"What is the main reason you work part-time?"* asked to part-time workers in the Labor Force Survey. The sample covers 144,904 workers between 2003 and 2023.
(b) The figure shows answers to the question *"Why do you want another job?"* asked to workers who report that they want another job (either in replacement or in addition to the current one) in the Labor Force Survey. Multiple answers are possible. The sample covers 94,573 workers between 2013 and 2023. The period is restricted to 2013-2023 for this question only in order to ensure the consistency of the variable across the years.

Figure B2: Worker Mobility in the EEC



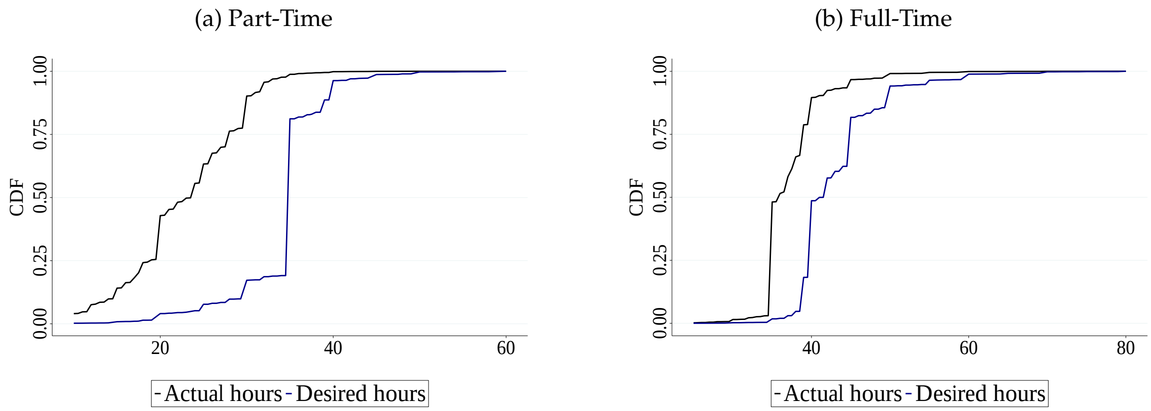
Note: This figure represents worker mobility patterns across quarterly rounds of interrogation in the Labor Force Survey. Workers are classified as unconstrained, top-constrained, or bottom-constrained based on their answer to the STPLC question during their first interrogation. See 2.1 for more details. The x-axis shows the rank of interrogation while the y-axis displays the share of workers who are not in the same workplace *(SIRET)* as in their first interrogation. The sample covers 717,544 workers between 2003 and 2023.

Distribution of Desired Hours. Figures B3a and B3b show the distributions of desired hours, as compared to actual hours, respectively for part-time and full-time constrained workers. Figure B3a shows a clear jump in desired hours around 35 hours for part-time workers, indicating that many constrained part-time workers want to move to full-time status. This suggests significant involuntary part-time employment among workers who cannot achieve their preferred hours. Reassuringly, both panels show substantial variation in desired hours rather than excessive clustering at round numbers, e.g. like 40. This suggests that workers are genuinely reporting their true preferences rather than simply picking salient thresholds and lends credibility to the desired hours measure as capturing meaningful heterogeneity in workers' preferences.

B.2 Measurement of Hours Worked in French Administrative Data

This section aims to assess the reliability of working hours reported in the French matched employer-employee data (DADS). Those administrative datasets cover almost the entire salaried workforce and have been widely used in labor market studies. Reporting hours in the DADS is mandatory and the information is used to manage and administer unemployment insurance and social benefits. To check the validity of hours, I rely on the methodology of Lachowska et al. (2022),

Figure B3: Distribution of Actual and Desired Hours, EEC 2003-2023



Note: The figures show the distributions of actual and desired hours worked for constrained workers based on Labor Force Surveys pooled between 2003 and 2023. The sample has been restricted to constrained employees with hours worked above 10 and an hourly wage between 0.8 and 1000 times the hourly minimum wage.

applied to the administrative data of the State of Washington, and extend it by incorporating elements specific to the French context. This methodology has become a standard procedure to evaluate the quality of hours data (see e.g. Labanca and Pozzoli (2022)).

As in the original paper, I first compare the distributions of hours worked in the administrative data and the Labor Force Survey, including on a common sample of workers. Although the definitions of hours worked differ according to the sources, this comparison highlights the degree of reliability of the variable according to the type of situation. Second, I measure the correlation between the evolution of annual earnings and hours worked for individuals who remain in the same job over two successive years of data, denoted as the "signal-to-noise" ratio in Lachowska et al. (2022). Assuming that their hourly wage should remain constant over time, the estimated coefficient should be relatively close to 1 (0.8 in the original paper). Third, I examine to what extent the lower end of the hourly wage distribution follows the evolution of the hourly minimum wage (the *Smic* in France) over time.

B.2.1 Hours Distributions in Admin and Survey Data

The first part compares the working hours distributions reported in the DADS and the Labor Force Survey, which is the main source of survey data for working time studies. I consider data for the years 2005, 2010, 2015, and 2019, covering the entire study period (2003-2023) while maintaining a manageable dataset size. Some restrictions are applied to the DADS data to limit measurement errors: workers aged between 15 and 64, in ordinary jobs of more than 120 hours and 60 days. I also keep one observation per person-year, the one with highest annual earnings to maintain consistency with the EEC definition of working hours *in the primary job*. Despite these adjustments, the comparison exercise has notable limitations.

First, the definition of hours worked is not the same across sources. The DADS data records the total number of paid hours for a given employer over the year. This definition is closer to contractual working time including standard hours, overtime, and paid absences. The EEC data, on the other hand, asks individuals about their *usual* hours worked (including overtime) per week. In short, the EEC aims to estimate the actual working time of the individual, including times that do not necessarily result in remuneration, while the DADS reflects the employer's perspective on the official hours of their employees. Annual hours from the DADS are recomputed as weekly hours using the starting and ending dates of employment. Second, the scope of the two sources differs. The DADS provides information on all salaried workers, while the EEC draws its sample from all individuals living in ordinary housing, including inactive or non-salaried individuals. I retain only salaried workers in this sample, although they are not representative of the entire population. To address potential sampling issues, I also provide distributions of both types of hours from the common EEC-DADS sample introduced in Section 2.3.

Figures B4a and B4b show the distributions of hours respectively from the DADS and the EEC. It is clear that the 35-hour peak, the standard duration in France, is more pronounced in administrative data, compensated by an over-representation of declarations between 37 and 45 hours in the EEC. Figure B5 compares both distributions in the common EEC-DADS sample. The profiles are very close to the original figures which suggests that the gap in hours is not driven by representativeness issues. Figure B6 represents average DADS paid hours at each level of EEC usual hours. Values are very close to the $x = y$ line in the part-time space (below 35) while in the full-time case both measures show very limited correlation. This may reflect that employees do not integrate well their

Two particularities of the French working time regulation system can help to explain the difference. First, *forfait jours* contracts are a French flexible work arrangement which entails that working time is measured in terms of annual working days rather than in weekly hours. For workers subject to this arrangement, about 15% of the workforce in 2019, the employer is not required to monitor hours worked, nor to report them in their DADS record. The absence of hours worked is circumvented by Insee through recoding to an arbitrary number of hours. Since 2017, a variable of the DADS dataset (UNITMESUREREF) allows to identify workers with a forfait jours contract. They turn out to be mainly attributed either 1820 or 2200 annual hours depending on the year of data. Forfait jours contracts are excluded from the sample in the majority of the paper and their removal is made explicit. Second, the gap in hours distributions between DADS and EEC could also be due to the *Réduction du Temps de Travail* (RTT) scheme. This arrangement grants rest days or half-days to an employee if the working time exceeds 35 hours per week (up to 39 hours weekly). Then, an employee who has a contract with 39 hours per week would probably report 39 usual hours in the EEC but their total number of hours over the year would correspond to a 35-hour equivalent. I argue that the RTT scheme and differences between employers and employees in their reporting nature explain the remaining gap in hours.

B.2.2 Signal-to-Noise Regressions

The hourly wage of a worker paid through an hours contract can be considered to fluctuate stochastically around a fixed hourly rate. This observation from Lachowska et al. (2022) suggests that a simple regression of the evolution of annual labor earnings in logs between two periods $[\Delta \ln(earn_{it})]$ on the equivalent change in terms of hours worked $[\Delta \ln(hrs_{it})]$ provides a test of the reliability of the measurement of hours:

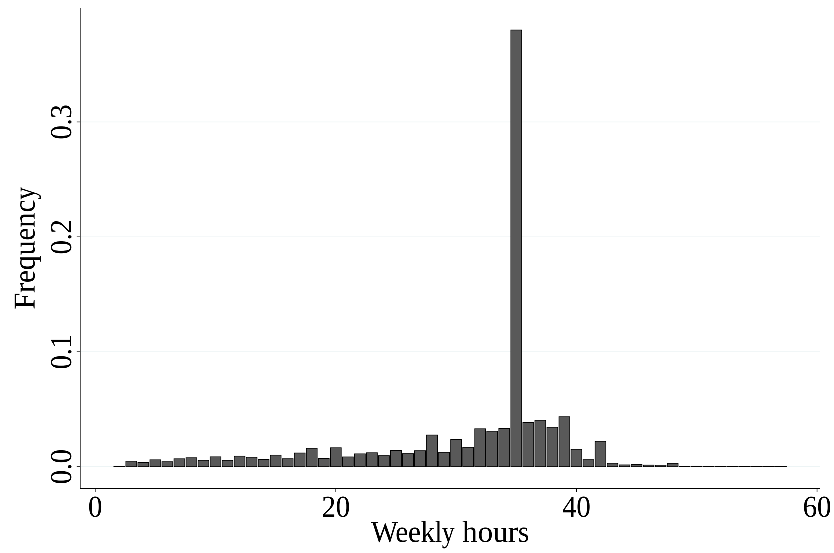
$$\Delta \ln(earn_{it}) = \alpha + \beta \Delta \ln(hrs_{it}) + \varepsilon_{it}$$

The test is not as relevant in the DADS yearly data as it is in the original Washington state quarterly data because hourly wages are more likely to increase e.g. due to promotion. Still, if hours are measured accurately, the estimates of the coefficient on the evolution of hours (β) should be arbitrarily close to 1 for hourly paid workers. On the other hand, if hours are measured with significant error, the coefficient from this simple regression is expected to be *attenuated*. Using the DADS yearly files between 2018 and 2019, I retain workers who stay in the same company and the same occupation across years and estimate the coefficient β in different specifications.

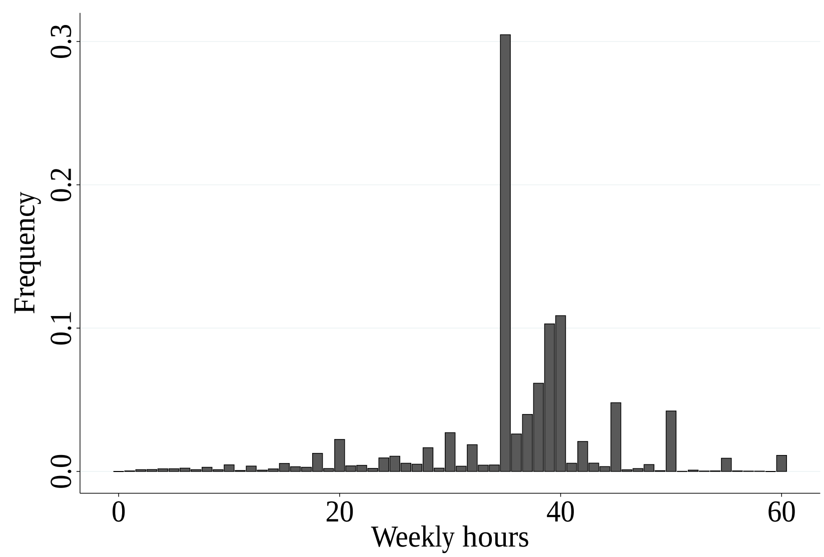
The results show a coefficient slightly below 0.7 stable across specifications. Complementary results by industry show strong homogeneity in signal-to-noise coefficients. Lachowska et al.

Figure B4: Distributions of Weekly Hours, EEC vs DADS, 2005, 2010, 2015 and 2019

(a) DADS - Paid hours



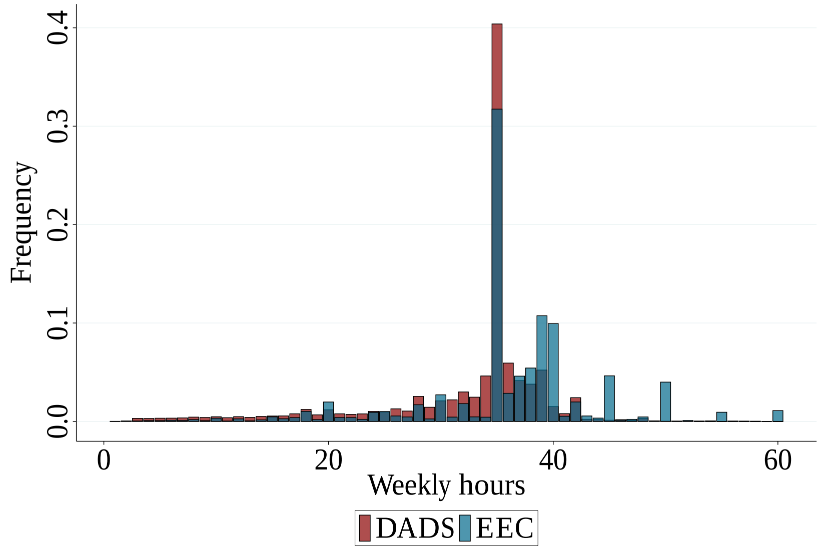
(b) EEC - Usual hours



Note: These figures show the distributions of weekly working hours in the DADS and the French Labor Force Survey (EEC) in years 2005, 2010, 2015 and 2019. The sample includes salaried workers aged 15-64 in ordinary jobs of more than 120 hours and 60 days. Annual paid hours from the DADS are recomputed as full-year equivalent using the employment duration and then divided by 52 and rounded to obtain weekly hours. Values above 60 are not displayed.

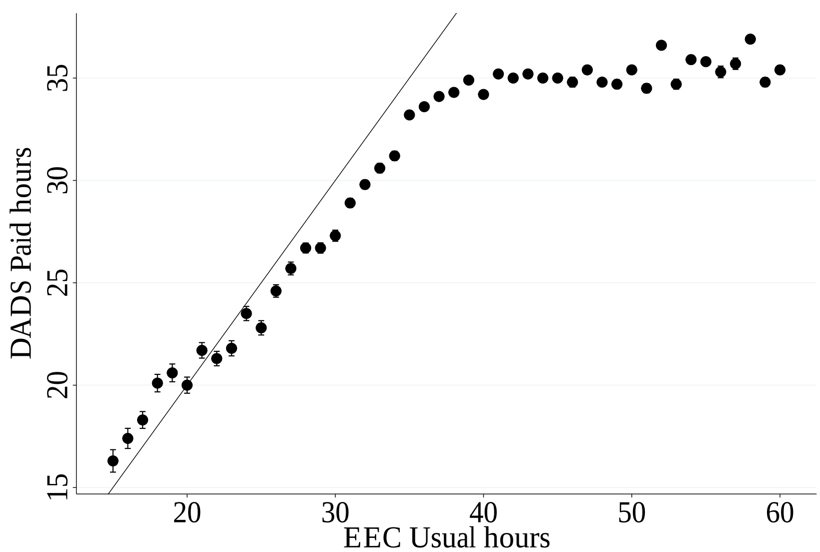
(2023) consider that a coefficient equal to 0.8, in an area with 63% hourly-paid workers indicates low measurement error in hours. The lower proportion of hourly-paid workers in France coupled with the yearly nature of the data partly explain the lower coefficient and suggest that the DADS

Figure B5: Distributions of Weekly Hours, EEC-DADS



Note: These figures show the distributions of weekly working hours in the EEC-DADS dataset between 2003 and 2023. The sample includes salaried workers aged 15-64 in ordinary jobs of more than 120 hours and 60 days. Annual paid hours from the DADS are recomputed as full-year equivalent using the employment duration and then divided by 52 and rounded to obtain weekly hours. Values above 60 are not displayed.

Figure B6: Comparison of Hours Worked, EEC-DADS



Note: These figures show the relation between DADS paid hours and EEC usual hours in the EEC-DADS dataset between 2003 and 2023. Values correspond to the average of DADS paid hours at each (rounded) level of EEC usual hours. The diagonal line has slope 1. The sample includes salaried workers aged 15-64 in ordinary jobs of more than 120 hours and 60 days. Annual paid hours from the DADS are recomputed as full-year equivalent using the employment duration and then divided by 52 and rounded to obtain weekly hours. EEC weekly hours below 15 and above 60 are not displayed. Error bars correspond to the coefficient of variation.

Table B1: Signal-to-Noise Coefficients between Earnings and Hours, 2018-2019

Dependent variable:	$\Delta \ln(earn_{it})$			
	(1)	(2)	(3)	(4)
$\Delta \ln(hrs_{it})$	0.684	0.684	0.692	0.692
	(0.000)	(0.001)	(0.002)	(0.001)
Employer FE	No	No	Yes	Yes
Std. Errors	Standard	Clustered at worker level	Standard	Clustered at worker level
Observations	12,608,316	12,608,316	12,608,316	12,608,316
Adj. R^2	0.49	0.49	0.62	0.62

Note: This table shows the results of the signal-to-noise regression using different specifications. The sample is composed of workers from the DADS 2018 annual dataset who stay with the same primary employer and the same occupation in 2019. Standard errors are in parentheses.

data could have a measurement quality similar to Washington state data.

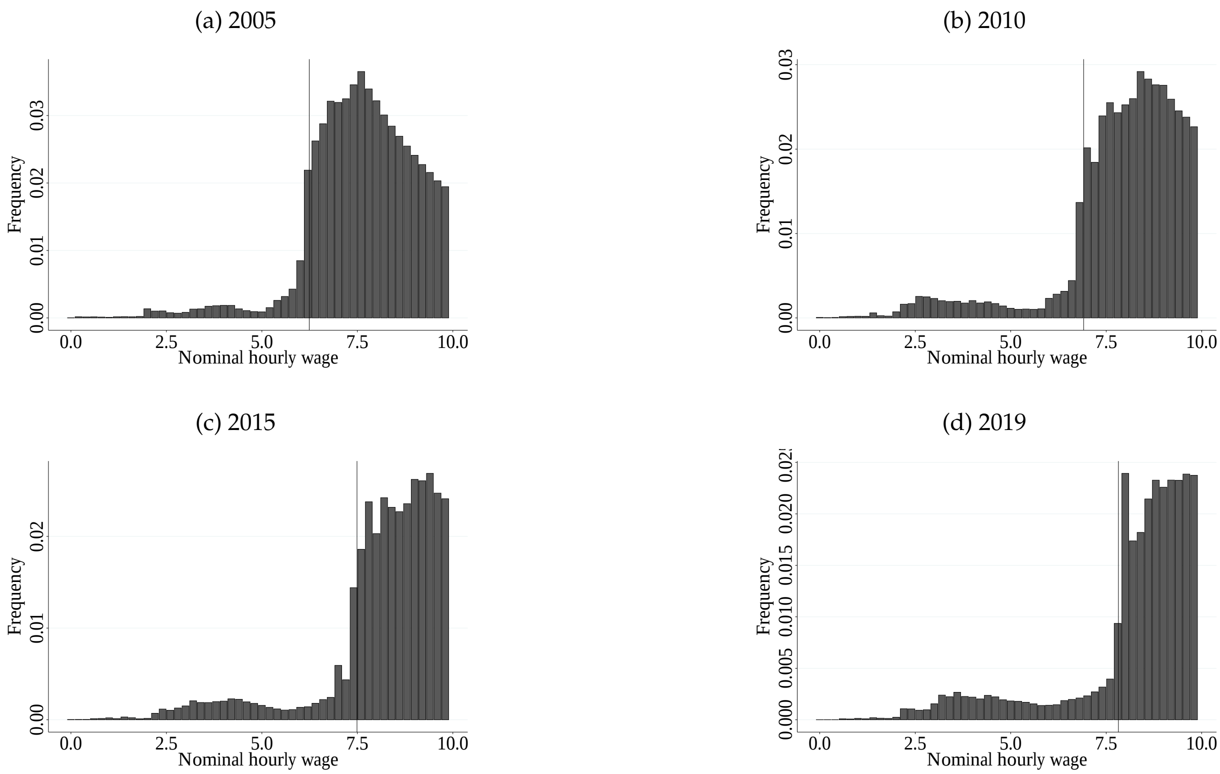
B.2.3 Minimum Wage Changes and Nominal Wage Distributions

A simple test of the reliability of working hours, at least for low-wage employees, is to observe whether the distribution of nominal hourly wages reflects the variations in the net hourly minimum wage (the *Smic horaire*) over time. The hourly minimum wage is indexed to the inflation rate measured for workers below the first quintile of the earnings distribution. Figure B7 presents the results for 2005, 2010, 2015, and 2019. The distribution of hourly wages exhibits a shift in the concentration of wages over time that corresponds to variations in the net hourly minimum wage. This pattern would not be observable in a database with significant measurement error. In particular, this exercise rules out systematic, time-invariant reporting.

B.3 Matching EEC and DADS

This section describes the procedure for linking the French Labor Force Survey (EEC) with the French matched employer-employee dataset (DADS) at the individual level. The general approach consists of finding the individuals surveyed by the EEC in the DADS exhaustive records. The sample only includes perfectly identified individuals i.e. who appear in a 1-to-1 match. This sample is then connected to the DADS panel obtained by following the procedure of Godechot et al. (2023). This ultimately leads to an innovative EEC-DADS Panel combining 6 quarters of observation in the EEC with the worker's employment history.

Figure B7: Distribution of Hourly Wages and Minimum Wage



Note: These figures represent the distributions of nominal hourly wages around the net hourly minimum wage (the *Smic horaire*) in 2005, 2010, 2015 and 2019. Nominal hourly wages are obtained by dividing net annual earnings by the annual number of hours worked in the DADS. Black vertical lines correspond to the net hourly minimum wage for the respective year. The values for the hourly minimum wage (in current euros) are 6.24 (a), 6.91 (b), 7.49 (c) and 7.82 (d). Distributions are divided into intervals of 0.20 euros and values above 10 euros are not displayed.

The challenge of matching the French Labor Force Survey with the DADS lies in the absence of a common individual identifier. However, both datasets share a number of variables that are supposed to be consistent: age, sex, occupation, part-time/full-time work, birth department, birth month (only between 2009 and 2012), residence municipality, and establishment's ID (*SIRET*). Table B2 reports the names of the variables. The *SIRET* is the key variable that makes this match feasible, as it considerably reduces the number of individuals with the same characteristics and therefore limits the risk of ”1-to-many” matches. Age (at the end of the year) and sex are never missing and have no reason to differ across sources for a given individual. The combination of these three variables is the base of the matching procedure and already provides a strong identifier, as ”1-to-many” matches would only occur if there are at least two individuals of the same age and gender who work in the same workplace during the same year. Other variables are more subject to misreporting and are thus at some point recoded or removed from the list of matching variables. The idea is to use all common variables to build a correspondence table between individual identifiers of both sources for each year. Importantly, the EEC information concerns the primary job of the employee, which means that the linkage is realized through this employment spell. But, once an individual has been matched and appears in the correspondence table, all their employment spells during the year can be recovered from the DADS.

Table B2: Variables for EEC-DADS Matching

Variable	**EEC**	**DADS**	**Description**
Establishment's ID	SIRET	SIRET	The SIRET is a unique identifier for establishments in France. In the EEC, the variable is coded by Insee based on the establishment's adress reported by the individual. In the DADS, it is directly reported by HR services.
Age	AG	AGE	Age of the individual at the end of the year.
Sex	SEXE	SEXE	Gender of the individual (male/female classification).
Occupation	CSTOT, P	CS, PCS	The French occupational classification system changed in 2008. 2-digit variables are used prior to 2009 (CSTOT in the EEC and CS in the DADS), while the 4-digit current system variables (P in the EEC and PCS in the DADS) are used afterwards.
Working Time Status	TPPRED	CPFD	Employment status (full-time or part-time).
Birth Department	DNAI	DEP_NAISS	French *départment* (101 values) where the individual was born.
Birth Month (2009-2012)	NAIM	MOIS_NAISSANCE	Month of birth, available only for the specified period in the DADS.
Municipality of Residence	DEPCOM	COMR	French municipality, identified by the *Code commune*, where the individual resides.

Note: This table contains the names and description of variables used to link the EEC and DADS datasets. Variable names correspond to the 2019 version of each dataset (except for occupation and birth month). Multiple revisions between 2003 and 2023 have induced changes in the names and content of several variables. These changes are taken into account in the cleaning process in order to build a version consistent over the years.

The procedure starts with some minor cleaning of the EEC to make some variables consistent with their DADS equivalent. All quarterly files between 2003 and 2023 are pooled, restricting the sample to employees whose *SIRET* information is not missing - about 81% of the sample (see

Table A1). Likewise, the regional DADS files are pooled to build yearly DADS datasets with the minimum required number of variables (the individual ID *IDENT_S* and the matching variables). The match is then performed in multiple steps with different subsets of the set of matching variables in order to optimize "1-to-1" matches. Here are the 11 sets of variables used through the procedure (using the DADS labels reported in Table B2):

- **Set 1:** SIRET, AGE, SEXE, PCS, CPFD, DEP_NAISS, COMR
- **Set 2:** SIRET, AGE, SEXE, PCS, CPFD, COMR
- **Set 3:** SIRET, AGE, SEXE, PCS, CPFD, DEP_NAISS
- **Set 4:** SIRET, AGE, SEXE, CPFD, DEP_NAISS, COMR
- **Set 5:** SIRET, AGE, SEXE, CS, CPFD, DEP_NAISS, COMR
- **Set 6:** SIRET, AGE, SEXE, CS, CPFD, COMR
- **Set 7:** SIRET, AGE, SEXE, CS, CPFD, DEP_NAISS
- **Set 8:** SIRET, AGE, SEXE, CS 1st digit, DEP_NAISS, COMR
- **Set 9:** SIRET, AGE, SEXE, CPFD, DEP_NAISS
- **Set 10:** SIRET, AGE, SEXE, DEP_NAISS
- **Set 11 (2009-2012):** SIRET, AGE, SEXE, MOIS_NAISSANCE

The match is run with a R script called `2_eecdads_id.R` at the yearly level using clean and appended EEC and DADS files. At each step, I remove from both datasets individuals who have already been matched in order to avoid double matching. The complete process yields a correspondence table for each year between unique identifiers from the EEC (*IDENT* $\times$ *NOI*) and the DADS (*IDENT_S*). Using the correspondence table, one can retrieve all observations of identified individuals in the EEC and the DADS yearly files to build the EEC-DADS sample.